THREE ESSAYS ON CHILD HEALTH AND SKILL FORMATION

BY

Sumanta Mukherjee

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Chairperson: Donna K. Ginther

Joshua L. Rosenbloom

Ronald C. Caldwell

William Darity

ChangHwan Kim

Date Defended: April 15, 2011

The Dissertation Committee for Sumanta Mukherjee

certifies that this is the approved version of the following dissertation:

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Chairperson: Donna K. Ginther

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Abstract

This dissertation attempts to add to the scholarly literature on parental investments in children. In particular, these essays study a number of ways in which children use their time, and the potential influence of such use of time on the development of cognitive and non-cognitive skills in school-age children in the U.S. and in India. The particular uses of time that this dissertation addresses include participation in lessons and sports, spending time with mothers, and spending time away from school to support family members. The key difficulty in identifying a causal impact of these choices arises from the possibility that a child's human capital acquisition decisions are made jointly with a variety of other decisions. To deal with potential endogeneity in these analyses, I employ a number of empirical techniques: individual fixed effects, sibling fixed effects, and instrumental variables. The first essay examines the impact of parental choices regarding extra-curricular activities on the health and skill acquisition outcomes of school-age children in the US. Using longitudinal time use data from the Child Development Supplement (CDS) of the PSID, I find reduced behavioral problems and enhanced positive development for children that engage in structured activity. Participation in lessons also significantly increases positive behavior and mathematics test scores. In the second essay, data on a panel of children aged five through eighteen from the NLSY-Child (1979) are analyzed to explore the effect of maternal employment on a child's mental health outcomes. Using fixed effects estimates, we find that mothers who spend more time at home have children with fewer emotional problems: they score lower on the behavioral problems index; they are also less likely to be frequently unhappy or depressed. In the final essay, cross-section data drawn from the 50th Round of the National Sample Survey (NSS) from rural India are analyzed to explore the relationship between fertility and child labor. Our results indicate the possibility of a *sibling subsidization effect*: all else equal, a new child in the family results in increasing the probability of sending an oldest child in the age group 5-14 out to work by over 5%.

To the memory of my mother

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More people have helped me write this dissertation than I could possibly mention here. Some of them go back to the time when I was leaving high school in India; some of the others, I did not even know until a few months ago. My friends that I will not mention here are not forgotten: I thank them all from the bottom of my heart.

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Three Essays on Child Health and Skill Formation

Sumanta Mukherjee[1]

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Doctoral Dissertation

Principal Supervisor: **Prof. Donna K. Ginther**[2]

[1] Department of Economics, University of Kansas, 318 Snow Hall, 1460 Jayhawk Blvd., Lawrence, KS 66045 (email: mukherjee@ku.edu).

[2] Department of Economics, University of Kansas, 333 Snow Hall, 1460 Jayhawk Blvd., Lawrence, KS 66045 (email: dginther@ku.edu).

INTRODUCTION

Over the last three decades, a growing body of scholarly literature has analyzed child outcomes.[3] However, in spite of growing awareness, the myriad processes that shape children's health and skill formation are not fully understood. In these essays, I try to analyze at least some of the potential factors that influence these particular human capital outcomes for children. In the first two essays, I focus on the determinants of non-cognitive development for school-age children in the US. In particular, the first essay examines the effect of structured activity on non-cognitive skill formation, while the second analyzes the causal link between maternal employment and non-cognitive skill deficiency of children. In the final essay, I attempt to bring an international perspective to my analysis and study the phenomenon of child labor in India. In particular, we ask whether fertility choices are instrumental in perpetuating child labor.

In the context of human capital acquisition for school-age children, the phenomenon of child labor presents a unique issue: while time at work reduces time at school, it is unclear whether it unequivocally impedes human capital formation in children. The low rate of return from schooling, coupled with the opportunity to learn a useful trade make working lucrative for a child and can potentially augment her human capital. So, while the first two essays identify potential impediments to human capital acquisition, the third essay only identifies the link between parental choices and child work, without suggesting that these choices necessarily inhibit human capital acquisition.

Identifying the *causal* effect of these determinants can be challenging. The key difficulty in disentangling the relationships arises from the possibility that a child's human capital

[3] Haveman and Wolfe (1995) provide an early survey of the extensive interdisciplinary literature on the determinants of child outcomes.

acquisition decisions are made jointly with a variety of other decisions. While some of these choices are observable, there may be many unobserved processes that jointly determine both the outcomes and the explanatory variables. To deal with potential endogeneity in these analyses, I employ a couple of empirical techniques. In the first two essays, I use two nationally representative datasets: the PSID-Child and the NLSY-Child (1979). The longitudinal structures of these datasets provide the opportunity to study individuals over a period of time, and thereby help in eliminating time-invariant unobserved effects that could potentially bias the estimates. In the third essay, we use the 50^{th} Round data from the National Sample Survey of India. It is a nationally representative household survey undertaken every five years. We use an instrumental variable to identify the causal link between fertility and child labor.

The first essay examines the impact of parental choices regarding extra-curricular activities on the health and skill acquisition outcomes of school-age children in the US. In particular, I focus on children's participation in structured activity, lessons, and sports. Using rich longitudinal time use data from the first two waves of the Child Development Supplement (CDS) of the PSID, I estimate individual fixed effect models to analyze the causal effect of these choices on several non-cognitive, cognitive and physical health outcomes. The results show reduced behavioral problems and enhanced positive development for children that engage in structured activity. Children that participate in structured activity also have higher mathematics test scores. Participation in lessons also significantly increases positive behavior and mathematics test scores. Finally, I find no effect of a child's participation in lessons or structured activity on body mass in fixed effect models, although there is a strong negative association in OLS models. The causal effects of these choices on measures of cognitive and non-cognitive outcomes suggest important avenues for parental intervention in child development.

An extensive literature has analyzed the effect of a mother's employment on cognitive outcomes of her children. However, the role of maternal employment in a child's non-cognitive development has received comparatively scant attention. In the second essay, data on a panel of children aged five through eighteen from the NLSY-Child (1979) are analyzed to explore the effect of maternal employment on a child's mental health outcomes. Using ordinary least squares and fixed effects estimates, we find that mothers who spend more time at home have children with fewer emotional problems: they score lower on the behavioral problems index; they are also less likely to be frequently unhappy or depressed. In addition, children with mothers spending more time at home are less likely to hurt someone, steal something, or skip school.

In the final essay, cross-section data drawn from the 50th Round of the National Sample Survey (NSS) from rural India are analyzed to explore the relationship between fertility and child labor. Potential endogeneity issues are addressed using an instrument that is premised on the preference for male children in rural India. Our results indicate the possibility of a *sibling subsidization effect*: all else equal, a new child in the family results in increasing the probability of an older child out to work by over 5%.

The paper is divided into three essays. In each essay, I first survey the existing literature before outlining the estimation strategies. Subsequent subsections describe the datasets, explain the included variables, and report descriptive statistics. The final subsections report regression estimates and robustness checks.

Essay 1

What Caregivers Should Care About: Parenting and Human Capital Formation

Sumanta Mukherjee

University of Kansas

1. INTRODUCTION

Over the last three decades, a growing body of scholarly literature on investments in children has analyzed child outcomes.[4] However, this literature is characterized by the widespread use of some measure of a child's cognitive ability as the primary outcome. Cognitive development is typically captured by standardized test scores (such as the PIAT Math and Reading), with little emphasis on non-cognitive outcomes.[5] The recent literature on human capital however argues that in addition to cognitive skills, a variety of non-cognitive skills are also crucial determinants of subsequent socioeconomic success (Heckman and Krueger, 2003). Heckman *et al* challenge the conventional view that equates skill with intelligence, adding that "numerous instances can be cited of people with high IQs who fail to achieve success in life because they lacked self-discipline and of people with low IQs who succeeded by virtue of persistence, reliability and self-discipline" (Heckman and Rubinstein, 2001). They cite social skills, motivation, time preference and other non-cognitive skills (in addition to basic intelligence) as key to labor market success. In the same vein, Cairneiro *et al* (2005) argue that policies intended to promote racial and ethnic equality should seek to influence the more malleable behavioral abilities in addition to their cognitive counterparts. Heckman's concern is reflected in a small but growing literature that attempts to identify the proximate determinants of adolescents' non-cognitive skills.[6]

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[4] Haveman and Wolfe (1995) provide an early survey of the extensive interdisciplinary literature on the determinants of child outcomes.

[5] Bernal and Keane (2006) surveys a large literature on child outcomes (particularly as a consequence of maternal employment). The survey reveals the strong bias in favor of test scores as the primary measure of child outcomes.

[6] Aizer (2004); Cunha and Heckman (2008); Heckman *et al* (2001, 2002, 2006) are important examples.

In addition, growing rates of child obesity have garnered wide attention from economists, healthcare professionals and health policy experts. This surge in obesity research is motivated by the range of health problems (including mortality risks) associated with obesity.[7] Childhood obesity, while rarely fatal, is itself associated with increases in 'type 2' diabetes, high blood lipids, hypertension, sleep apnea, orthopedic problems and early maturation (Ebbeling *et al* 2002). Susceptibility to these diseases potentially compromises an obese child's human capital and skill acquisition, thereby affecting subsequent earning capacity.[8]

The determinants of children's physical and emotional well-being have gained some ground in the recent economic literature on child development. However, in spite of growing awareness, the myriad processes that shape children's body mass and non-cognitive skill formation are not fully understood. To the extent that these outcomes are not viewed as being largely genetically determined, there is scope for public policy to identify and influence particular behavioral choices that determine child outcomes. For school-age children, many of these choices are either made explicitly by parents, or are shaped by the particular parenting environment the children grow up in. Parenting environment is, in turn, often determined by parents' personal preferences and resource constraints. For instance, children's participation in

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[7] According to McGinnis and Foege (1993) and Allison *et. al*. (1999), annually over 300,000 premature deaths in the US can be traced to obesity and sedentary lifestyle. Consumption of tobacco, the single largest factor associated with mortality in the US, leads to about 400,000 deaths annually in the US. This makes obesity and sedentary lifestyle second only to tobacco in causing premature deaths of Americans.

[8] Obese children are likely to consume more medical care than average, thereby incurring a substantial *private* cost. In addition, a *social* cost is incurred because the society bears a cost that the obese individuals did not take into account when making their decisions.

extracurricular activities or homework routine is largely influenced by the amount of time parents invest in their children.[9]

In view of the recent research that underscores the importance of non-cognitive skills in socio-economic success, in this paper I investigate potential channels through which children could acquire non-cognitive skills. In this paper I argue that one potential channel through which school-age children acquire non-cognitive skills is participation in structured activity, such as lessons and sports. Participation in sports or lessons takes time away from curricular work, but could also act as an important determinant of physical and psychosocial development. Time spent in structured activities is likely to encourage social skill, together with the development of discipline and team work, which may spill over to the traditional academic domain resulting in higher test scores and improved school performance. In this paper, I use longitudinal time use data from the Child Development Supplement of the PSID to analyze the effect of participation in structured activity on behavioral problems, positive development, measures of cognitive development and body mass. In my data I use the phrase 'structured activity' to include lessons in dance and gym, along with team and individual sports (such as soccer, athletics, swimming, yoga and martial arts).

The baseline ordinary least square estimates suggest a strong negative association between structured activity and behavioral problems. Participation in structured activity is also associated with higher scores in positive behavior scale, indicating development of non-cognitive skills. In addition, engaging in structured activity appears to be highly correlated with higher test scores in mathematics. This indicates that structured activity not only shapes non-cognitive

[9] A large literature examines the impact of parental resources (including income and time) on child outcomes. See, for instance, Blau and Grossberg (1992); Blau (1999); Dahl and Lochner (2005); Han *et al* (2001); James-Burdumy (2005); Lang and Zagorsky (2001); Ruhm (2004); Shea (2000); Waldfogel *et al* (2002).

skills, but also augments cognitive development. Lessons in dance, sports and gym are associated with increased mathematics test scores and positive behavior, but have no significant correlation with behavioral problems or body mass.

While the ordinary least squares models indicate important associations, identifying the causal impact of the proposed determinants can be challenging. The key difficulty in disentangling these relationships arises from the possibility that a child's human capital acquisition decisions are made jointly with a number of related parental choices. While some of these choices are observable (such as parental occupational engagement, or school choice), there are many unobserved processes that jointly determine both the outcomes and the explanatory variables. To eliminate *time-invariant* unobserved heterogeneity, I exploit the longitudinal nature of the Child Development Supplement and estimate individual fixed effect models. The results are broadly similar to the baseline coefficients. In particular, the results show reduced behavioral problems and enhanced positive behavior for children that engage in structured activity. Children that participate in structured activity also have higher math test scores. These effects are strongly significant for boys and whites; for girls and African-Americans, the coefficients are not significant although they have the expected signs. In addition, lesson participation significantly increases positive behavior and math test scores for all samples except the African-Americans. Finally, I find no effect of a child's participation in lessons or structured activity on body mass in the individual fixed effect models for any sample.

The key point that these results underscore is the importance of parental intervention in child development. Choices involving participation in structured activity and lessons are largely influenced by the parents' personal priorities and resources. Having a child participate in meet sports or dance lessons entails some time commitment for the child's caregiver (for arranging transportation on practice days, as well as for attending final matches and performances). The caregiver’s work schedule along with her own priorities could then crucially influence the participation decision. The causal effect of behavioral choices like structured activity participation on non-cognitive skills and test scores in children suggests important avenues in which caregiver monitoring and encouragement can induce favorable child outcomes in the short and the longer term.

2. STRUCTURED ACTIVITY: IMPLICATIONS FOR CHILD OUTCOMES

Time spent in extracurricular activity may crowd out academic work or other beneficial activities like volunteering (Coleman, 1961). But it may also crowd out potentially harmful activities such as experimenting with drugs and alcohol, and engaging in crime or sexual activity. Therefore, the ultimate effect of time spent in sports and/or extracurricular lessons is an empirical issue. Recent research suggests large positive associations between labor market returns and non-classroom oriented activities, such as sports participation. Persico, Postlewaite and Silverman (2004) find that taller teens earn a wage premium, and suggest that much of this height premium is mediated through participation in school athletics. The authors estimate a 2.6 percent increase in adult wages with an additional inch of height in high school. Adding controls for athletic participation reduces the coefficient estimate by a little more than a third and it becomes statistically indistinguishable from zero. Many other studies have documented a positive correlation between participation in high school athletics and wages in later life.[10] In a recent study Stevenson (2007) shows that sports participation leads to increases in college attendance and labor force participation for women.

What drives this positive association? There are at least two potential explanations. One possibility is that participation in lessons and sports may foster development of key skills that shape success in school. Any form of sport is typically a highly regulated system in which social conflict is displayed in positive light. Sports as well as lessons help children in learning to compete, and to operate successfully under a formal code of rules and procedures. In addition, they help children learn the importance of cooperation and teamwork. Recent research suggests

[10] These studies include McCormick and Tinsley (1987); Long and Caudill (1991); Maloney and McCormick (1993); Barron, Ewing and Waddell (2000).

the importance of these non-cognitive skills in determining labor market outcomes (Heckman *et al*, 2006). The alternative possibility is that higher ability students self-select into lessons and sports. Therefore, even if participation in these activities has a negative impact, one could still see a positive association between structured activity participation and labor market success.

In view of these issues, I attempt to examine whether participating in structured activity leads to non-cognitive skill acquisition that would eventually translate into increased labor market returns. This research is distinguished from existing studies in a number of ways. I use structured activity as the key explanatory variable, which combines all lessons and (team and individual) sports together. In order to better understand the processes that shape non-cognitive skill formation, I also estimate separate models for lessons and sports.

A number of studies analyze the impact of sports participation on wages. But these studies fail to identify the exact channels through which sports participation affect wages. Instead of concentrating on labor market returns, I focus on the development of skills that current research identifies as key in shaping labor market success. In particular, I focus on the determinants of non-cognitive (as well as cognitive) skills because these are known to translate into higher wages. By establishing that structured activity participation enhances these skills, I identify a potential process that can be influenced by parental intervention.

Finally, by exploiting rich longitudinal data I attempt to assign causality to the correlations documented in existing studies. I argue that by using individual fixed effects I can eliminate time-invariant unobservable heterogeneity, while controlling for a rich set of time-varying observable factors that potentially influence child outcomes. To the extent that key unobservable factors do not change over time, my model consistently estimates the effect of structured activity participation on child outcomes.

3. EMPIRICAL FRAMEWORK

The econometric models employed in this analysis are premised on economic models of the family as a production entity as delineated in Becker (1967, 1981), Becker and Tomes (1979, 1986) and Leibowitz (1974). These economic models portray households as productive entities where parents allocate resources (such as income and time) to maximize an objective function that includes the health and development of children as arguments. I use the first two waves of the longitudinal PSID-Child data for to analyze the impact of parental choices regarding structured activity and lesson participation on different measures of child outcomes. The baseline empirical models are pooled OLS regressions of a child's outcome variable (*y*) in year *t* on an indicator variable for participation (*P*) in a structured activity or lesson. But the estimates obtained from these models may be subject to bias, because: (i) there may be some additional factors that determine the outcome (such as food intake, that may influence body mass); and/or (ii) the children themselves may have certain individual preferences that determine their personal outcomes. To the extent that these traits are observable, they can be included as additional explanatory variables in the model. I therefore include a vector of explanatory variables (*X*) in my model that control for observable heterogeneity.

The parameter estimates may still be biased if there are unobservable processes that jointly influence both the explanatory and outcome variables. Assuming that such unobservable traits are time-invariant, I utilize the longitudinal structure of the PSID-Child data and specify individual (child) fixed-effects models to control for unobserved heterogeneity.

The individual fixed-effects model is specified as follows:

$$y_{jt} = X_{jt}\alpha + \beta P_{jt} + \theta_j + \varepsilon_{jt} \qquad (1),$$

where j indexes child, t indexes year, θ_j is the individual (child) fixed effect, ε_{jt} is the error term, and (α, β) are the parameters. The identifying assumptions are: (i) θ does not vary across years; and (ii) $E(P_{jt}\varepsilon_{jt}) = 0$ for all t. In other words, this specification assumes that the only source of correlation between the regressors and the disturbance is described by a covariate θ that does not change over time. Therefore taking first difference across time-periods, one can eliminate the unobserved time-invariant fixed-effect to obtain:

$$\Delta y_j = \alpha \Delta X_j + \beta \Delta P_j + \Delta \varepsilon_j \qquad (2).$$

OLS estimates of (2) are consistent for the parameters of interest. The key identification condition is that explanatory variable P_{jt} is time-varying. Therefore the model is identified by changes in structured activity or lesson participation over time.

Fixed effects models have the obvious advantage over OLS models in that they are able to control for unobserved and *unchanging* characteristics that are related to both the outcome and causing variables. But it is important to recognize the potential drawbacks of fixed-effect models. The bias from measurement error is usually aggravated by transformations that eliminate unobservable heterogeneity (Angrist and Krueger, 1998). More importantly, fixed-effect models assume that the only source of correlation between the regressors and the disturbance term is the *time-invariant* fixed-effect.[11] Inevitably, fixed-effects models therefore eliminate the effect of some important explanatory variables such as race and gender that are (presumably) time-invariant. I therefore split the sample by race and gender to understand how the coefficients compare across these subsamples.

[11] Parameter estimates in these models could be biased if the unobservable characteristics themselves change over time.

4. DATA AND DESCRIPTIVE STATISTICS

4.1 DATA

The Panel Study of Income Dynamics (PSID) is a longitudinal survey of a representative sample of American families. Data on employment, income, wealth, housing, food expenditures, income transfers, marriage and children have been collected annually since 1968. In 1997 the study shifted from annual to biennial data collection. In addition, in 1997, the PSID added the Child Development Supplement (CDS), a study of children aged 0-12 in a sub-sample of PSID families. The study mainly used existing measures to assess children and individuals close to them (including their main caregivers and teachers). Children's well-being was defined in terms of cognitive/academic, emotional/mental, social and physical development. The CDS has followed 2,705 eligible households (2,458 core and 247 from new immigrant sample) since 1997. Up to two children from each household were eligible to participate. The final CDS-I sample included 3,563 children in 1997. In the second wave administered between October 2002 and May 2003, CDS-II essentially followed the sample children of CDS-I whose families were still active in the PSID 2001 main study. A three-point eligibility criterion was applied for inclusion in the second wave which resulted in the attrition of 292 children.[12] Following the three-point eligibility criteria, the CDS-II data collection resulted in completed interviews for 2907 children with a response rate of 91 percent.[13]

[12] The eligibility criteria for inclusion in the second wave of CDS were: (a) response in CDS-I (n = 3,563); (b) considered sample at the time of the main PSID data collection in 2001 (n = 3,480); and (c) family of targeted CDS child still active in the PSID panel as of the 2001 main interview (n = 3,271).

[13] Follow-up interviews were attempted only if: (a) sample child still resided under the care of a primary caregiver; (b) sample child lived in the US; (c) sample child did not reside on a military base; and (d) sample child was non-institutionalized.

Each CDS child could have up to eight modules of data collected from three different family members and a school resource. I have used four of these eight modules in my study: the Primary Caregiver Child (PCG-Child), the Primary Caregiver Household (PCG-Household), the Child Interview and the Time Diaries. The primary module is the Primary Caregiver (PCG) Child Interview, which provides anchor information about target children. PCGs also provided household level information, such as income and race in the household interviews of primary caregivers. Children who were eight years of age and older were eligible to participate in an in-home interview themselves. This interview asked children about health behaviors, electronic media use and emotional well-being.

In addition, time diary data were obtained directly from the children or from the children with input from the caregiver, or, for very young children, solely from the caregiver report. The diaries were originally mailed out and the difficulties respondents had in completing them led to follow-up telephone interviews in which trained interviewers recorded most of the diary answers given by the caregiver/child. While the primary caregiver and child interviews included stylized questions about the children's cognitive outcomes and interaction with parents, the time diaries provided detailed accounting of the type, number and duration of activities during sampled 24-hour days, beginning at midnight for one randomly sampled weekday and one randomly sampled weekend day. For each activity reported, respondents were asked to provide information about (1) the time the activity began and ended, (2) where the child was during that activity, (3) who was doing that activity directly with the child (active engagement), (4) who else was there but not directly involved in that activity (passive engagement or accessible time), and (5) what else was the child doing along with the primary activity – the secondary activity. In order to obtain the most complete information possible for the target day, field interviewers contacted respondents to review the diaries. When there were gaps in the times given or when the diaries were incorrectly completed, the interviewers probed for additional information from the respondents.

4.2 DESCRIPTIVE STATISTICS

In this paper, I use the first two waves (1997 and 2002) of the CDS data. Table 1 outlines the important variables and provides summary statistics. My sample consists of 2,774 children (matched with their parents) that belonged in the age group five through seventeen in 2002, for whom time diaries were available in both waves. The outcome variables of interest are: (i) the behavioral problems index (BPI); (ii) the positive behavior scale; (iii) the body mass index for age (BMI for age); and (iv) standardized test scores for mathematics and reading. Table 1 summarizes the descriptive statistics of the key variables in my models.

The behavioral problems index is a scale constructed from thirty-two instruments administered to the primary caregiver to assess the incidence and severity of behavioral problems (both aggressive and withdrawn behavior) among children. The positive behavior scale is a mean score of ten items that measure the positive aspects of children's lives, including self esteem, social confidence, self-control, obedience/compliance and persistence. The positive behavior scale captures key non-cognitive skills that Heckman *et al* (2006) consider important inputs in socio-economic success. Lifestyle choices that influence these scores can therefore be expected to ultimately shape subsequent socioeconomic trajectories of these children. Cognitive development is captured by Reading and Mathematics standardized scores.[14] Physical health outcomes are broadly proxied by the body mass index. The BMI used here is called the BMI-for-age, because BMI for children and adolescents take into account age and gender in addition to height and weight. The mean BMI-for-age in my sample is a little under 20, although there is a fairly large variance in it as indicated both by its range and the standard deviation.

Several demographic, education and income characteristics that may influence cognitive and non-cognitive skill acquisition are included in my models. The various racial categories are constructed using primary caregiver reported values in 1997.[15] In the probability weighted sample, I have about 65 percent White children, while about 15 percent are African-Americans. Detailed family structure categories are constructed using information on PSID family information of the parents and caregivers of the target child. The underlying idea for including explicit family structure covariates is to capture the effect of the parental monitoring environment on child development. In my sample, 72 percent children grow up in traditional families (with both biological parents), whereas 21 percent grow up with single parents. Only about 6 percent have step parents, while about 1 percent grow up without any biological parent. About a third of the children in my sample have mothers that finished high school, while almost half have mothers that went to college. It is interesting to note that while mother's education is usually given for most children, there are some mothers that have acquired more education between 1997 and 2002. Therefore it is, in fact, a time-varying covariate in this sample.

[14] I use Passage Comprehension Standard Score to measure reading ability. An alternative measure, Broad Reading, did not have standardized scores. Mathematical aptitude is captured by Applied Problems Standardized Score.

[15] Racial information was again collected in 2002 directly from the Child Interviews. There were some disparities across the two waves, possibly because some children preferred to identify with a racial group different from the one reported by their PCG in 1997. In order to avoid any confusion I impute the 1997 race value onto the 2002 sample, thereby effectively ignoring the responses made by the children about their preferred racial affiliation.

I analyze certain behavioral choices that are likely to influence the above outcomes. I primarily focus on the participation in structured extra-curricular activity (lessons, individual and team sports). In order to better understand the effect of all structured activity, I also divide it into lessons and sports, and study their individual impact on child outcomes. Information on these activities is available from the detailed three-digit time diary aggregates. While time diaries provide detailed reports on the amount of time (measured in seconds) spent in each activity, these data are susceptible to measurement errors. In order to minimize measurement problems, I only use participation rates in various activities. I treat children as participating in an activity if they report positive amount of time spent in performing it. In my sample about 38 percent children report being involved in any structured activity.

Using time diary data from PSID-CDS to identify participation in structured activities potentially generates an additional analytical shortcoming. As mentioned earlier, for each child, a random school day (Monday through Friday) and a random weekend day (Saturday or Sunday) is recorded in a diary. If the randomly chosen day coincides with the day that the child engages in structured activity, the time diaries accurately capture the participation and also indicate the amount of time spent on it. However, if the structured activity is scheduled on a different day than the randomly chosen time diary day, then no entries are noted for structured activity participation. Consequently, the child is erroneously assumed to not participate in any structured activity, simply because the randomly chosen day did not coincide with the day the structured activity is scheduled. Time diary data therefore underreports engagement in structured activities; indeed any analyses based on these data underestimate the impact of engagement in structured activities on outcomes of interest.

In Table 2, I investigate how these participation rates vary by year across demographic, education, and income categories. A comparison across years reveals that participation rates in lessons, sports and structured activity consistently declined over the years. While about 40 percent children reported being involved in structured activity in 1997, it declined to about 33 percent in 2002. To be sure, while 896 children participated in structured activity in 1997, only 795 continued that in 2002. Out of the 857 children that participated in sports in 1997, 770 were engaged in sports in 2002. Finally, lesson participation numbers also declined from 61 to 33. The differences in these numbers do not necessarily indicate true dropouts: it is possible that some children actually joined these activities in 2002, so that there may be more dropouts than what the simple difference would indicate. In other words, while the numbers suggest that 101 children dropped out of structured activity by 2002, the actual number of dropouts may be higher because there were possibly some new entrants into structured activity in 2002.

While these data do not provide any clear explanation for the reduced participation over time, a number of hypotheses explaining this phenomenon can be constructed. When children are young, they are often encouraged to participate in a variety of structured activities; however, as they grow older, only the better performers (both in sports and fine arts) are retained in the school team. In other words, a number of children are weeded out of structured activities based on the quality of their performances. A second hypothesis applies to participation in sports. Often children that engage in outdoor team sports sustain injuries, and this limits their future participation in sporting activities. An additional possibility is that many children simply lose interest in structured activities as they grow older, and consequently drop out of these activities. There could be many reasons for losing interest in an activity, including the lack of parental involvement and encouragement.

A comparison across races indicates that White children participate more in any activity than children belonging to other racial groups. Children with more educated parents participate in more structured activity. Parental education is a particularly strong determinant of lesson participation: children with college graduate mothers are three times more likely to engage in lessons than those with high school graduate mothers. I divided income-to-needs ratio into four quartiles to get a better sense of the effect of financial resources on participation rates. I find that children from wealthier families are more likely to participate in structured activity. The income effect is again significantly stronger for lesson participation. Finally I find that a larger proportion of boys participate in sports, as expected. However, participation rates in lessons are significantly higher for girls.

5. RESULTS

5.1. ORDINARY LEAST SQUARES ESTIMATES

The ordinary least squares estimates of the effects of structured activity participation on the five outcome variables (behavioral problems; positive behavior; reading score; mathematics score; and body mass) are presented in Table 3. Different types of structured activities are then divided into two broad categories: lessons and sports. Tables 4 and 5 report the OLS estimates for the effect of lessons and sports respectively on the five outcome variables listed above.

The results listed in Table 3 show a strong negative association between participation in structured activities and behavioral problems. In addition, children that engage in structured activities also have better self-esteem, persistence, and social confidence, as captured by higher scores on the positive behavior scale. Girls significantly outperform boys in both measures of non-cognitive development, with lower scores on behavioral problems and higher on positive behavior. Family plays a substantial role in non-cognitive skill development, as indicated by the positive and significant coefficients in the BPI model. African-American children score higher on the behavioral problems index, while Hispanic children perform better than their White counterparts in both measures of non-cognitive development.

Cognitive skill development is captured by reading and mathematics test scores. I find a positive and highly significant effect of structured activity participation on applied problem solving skills, although reading comprehension skills are not significantly correlated. Girls perform better than boys in reading comprehension, but are outperformed by boys in mathematics. Children belonging to families without both biological parents do worse in both reading and mathematics than those from traditional families. The effect, however, is pronounced only in the mathematics test score. Cognitive skills are highly correlated with race: White children outperform African-American and Hispanic children by a large and significant margin in both reading and mathematics test scores. Finally, as expected, I find body mass index to be negatively correlated with structured activity participation. Race plays an important role here as well: African-American and Hispanic children have significantly higher body mass compared to their White counterparts.

The development experience of a school-age child is often shaped by the resources and choices of caregivers. I use maternal employment to capture parental resources, and parental education as a broad proxy for the choice of parenting practices. I find maternal employment status has important emotional consequences for children. While mother’s labor market commitment reduces her time with the child, it also has positive income effects that ultimately result in lower behavioral problems and enhanced positive behavior for the child. However it is not associated with cognitive development, or physical health. Parental education, on the other hand, is strongly correlated with cognitive development of children. In particular, children with parents that did not go to college perform significantly worse in both reading and mathematics compared to those that had college graduate parents.

The OLS results follow broadly similar patterns for lesson and sports participation as summarized in Tables 4 and 5. Participation in lessons is strongly correlated with positive behavior, but has no significant impact on behavioral problems. Sports participation, on the other hand, significantly impacts both behavioral problems and positive development in expected ways. Both lessons and sports are associated with increased mathematics test scores, but have no significant influence on reading ability. As before, girls perform better than boys in non-cognitive skills and reading, while falling behind in mathematics. Children growing up in intact families score have comparably fewer behavioral problems. Hispanic children do better than both White and African-American children in measures of non-cognitive outcomes, but White children have significantly better reading and mathematics skills. In addition, parental education and employment have expected impact. Parents with fewer years of education have children with more behavioral problems and lower cognitive skills. Maternal employment reduces behavioral problems and enhances positive development. Finally, while lesson participation has no significant effect, I find sports participation to be associated with a significant reduction in body mass.

5.2 INDIVIDUAL FIXED EFFECTS ESTIMATES

Tables 6 through 8 report individual (child) fixed effect estimates of the effect of participation in structured activity, lessons and sports respectively. As indicated by the OLS estimates in Table 3, participation in structured activity is associated with reduced behavioral problems through increased personal discipline and team interaction. The strong negative correlation between structured activity and behavioral problems reported in the OLS estimates is somewhat weakened but still significant when I employ individual fixed effects. Children that participate in structured activity also score significantly higher on the positive behavior scale, possibly because structured activities typically bolster compliance, persistence, and self-control. In particular, children that engage in structured activities score 0.17 points higher on the positive behavior scale, which is statistically significant at the 1% level. Heckman *et al* (2006) argue that it is a combination of these particular non-cognitive skills that play a key role in subsequent labor market success. Engagement in structured activity also significantly raises mathematics test scores, which is a crucial indicator of cognitive skill acquisition. The fixed-effects results suggest that parental encouragement in participating in structured activities is potentially an important mechanism influencing both short term and long term outcomes for children.

To further explore the mechanism through which structured activity impacts child outcomes, I divided it into two groups: lessons and sports. Lessons include dance and gym, while sports encompass all team and individual sports (such as athletics and soccer) that the children report being involved in. Table 7 summarizes the effect of lesson participation on child outcomes. In line with the OLS estimates, I find that lesson participation does not affect behavioral problems, but significantly increases positive development with individual fixed effects. Children that engage in lessons score over a point higher on the positive development index than those that do not participate in lessons. Lessons also affect cognitive outcomes in the expected direction with a large positive impact on mathematics scores. These results suggest that time away from curricular activities do not necessarily hurt school performance; indeed they underscore important spillover effects of discipline and persistence learnt in extra-curricular lessons in shaping cognitive (as well as non-cognitive) outcomes.

Individual fixed effect results for sports participation are summarized in Table 8. With individual fixed effects, the strong negative correlation between sports and behavioral problems is diminished, although still significant. However, the positive OLS association between sports and positive behavior ceases to be significant when I use individual fixed effects. This suggests that the OLS correlation is driven mostly by unobserved factors that jointly influence sports participation choice and positive development. A similar pattern is indicated by the mathematics test score coefficient: while still positive, it is no longer significant. Finally as indicated in all the fixed effects estimates, body mass index is not significantly affected by participation in any extra-curricular activity. My results suggest that the benefits from engaging in extra-curricular lessons or structured activity work primarily through improvement of social skill, self-discipline, persistence, and obedience. These key traits characterize children with better cognitive outcomes. But more importantly, these skills learnt outside curriculum help the child in meeting subsequent challenges in the labor market.

5.3 ROBUSTNESS

The fixed effects estimates discussed above indicate important relationships between child outcomes and participation in structured activity and lessons for the full sample. In order to investigate the robustness of these results, I split the sample into gender and racial categories and employ the fixed effect models described in (1). Tables 9 through 14 summarize these results.

Table 9 compares individual fixed effects estimates of the effect of structured activity participation between boys and girls. While behavioral problems were significantly affected in the full sample, the coefficients cease to be significant for any of the gender subsamples. Participation in structured activity enhances positive behavior for both genders, but the effect for boys is stronger and significant. Maternal employment continues to have a positive and significant impact on positive behavior for both genders. Structured activity augments mathematics scores as before, although the effect is stronger and significant for boys. Parental education continues to be an important determinant of cognitive skill for both genders. I split the sample into the two major races, White and African-American, in Table 10. For White children, positive behavior and mathematics scores remain the outcome variables that are significantly impacted. While the signs of these coefficients are expected, the effects are not significant for

African-American children. In both tables, I find that growing up with more siblings at home results in increased positive behavior and higher mathematics test scores. Comparing with the results for the full sample it appears that they are fairly similar: the full sample results appear to be driven largely by Whites and boys.

Individual fixed effects estimates of the effect of lesson participation are compared across gender in 11. As in the full sample, I find no significant effect of lesson participation on behavioral problems for either boys or girls. Lesson participation however results in significantly higher scores on positive behavior scale for both genders, with a stronger impact for girls. In addition, lessons help in pulling up mathematics scores for both genders, with a significant effect for girls. Maternal work has a marginally significant positive effect on mathematics scores and positive behavior for boys, but does not have any impact on girls. Comparing results across races in Table 12, I find that lessons lead to a large significant improvement in positive behavior only for the White subsample, with almost no impact on African-American children. However, lessons bolster cognitive outcomes for African-Americans, with a significant effect on reading scores. White children that participate in lessons show a large significant improvement in their mathematics scores. The full sample results are therefore broadly comparable with the gender and race subsamples. Splitting the sample by race and gender, I find that lessons have stronger effects on Whites and girls.

Tables 13 and 14 investigate robustness of the effects of sports participation across gender and race categories. Sports participation has a marginally significant negative impact on behavioral problems in the full sample. However, this impact ceases to be significant for either boys or girls. In addition, while sports participation does not have any effect on positive behavior in the full sample, it does have a significant and strong positive effect for the boys. Sports participation appears to foster social skills and discipline for the boys, whereas girls respond strongly to lessons. Mathematics scores also show significant improvement for boys that participate in sports, but this effect is not shared by the girls. The fixed effects estimates lose their statistical significance for all outcome variables when the full sample is split by race. The large negative and marginally significant impact on behavioral problems for African-Americans provides the only exception.

6. CONCLUDING REMARKS

While a large literature has looked at returns to schooling, very little attention has been given to understanding the processes that generate these returns. Recent research on the technology of skill formation points to the importance of both cognitive and non-cognitive skills, along with physical health in shaping labor market outcomes. In this paper, I analyze a potential channel through which school-age children acquire these key skills. I find that participation in structured extracurricular activities including lessons and sports leads to important gains in acquisition of both cognitive and non-cognitive skills. In particular, I show that participating in structured activities reduces behavioral problems and increases positive development and mathematics scores. However, I do not find any significant effect on body mass index.

It is however important to remember the potential shortcomings of this study. As mentioned earlier, fixed effects models are only able to control for unobserved and *unchanging* characteristics that are related to both the outcome and causing variables. Parameter estimates in these models could therefore be biased if the unobservable characteristics themselves change over time. Additionally, data from time diaries can be informative but prone to measurement errors. In view of that, I use only participation rates (as opposed to duration of activity) to minimize measurement error problems. The final caveat, as mentioned earlier, relates to the potential underestimation of the effect of structured activity participation. The participation rates and hence the parameter estimates provide a lower bound for the actual numbers.

With these caveats in place, we recognize that the results suggest an important channel for developing useful cognitive and non-cognitive skills. Participating in structured activity has strong effects on acquiring these skills. For school-age children, participation in structured activity is shaped largely by parental preferences and (time) constraints. To the extent that children learn key skills in these extracurricular activities, these results suggest an important avenue for parental intervention that can have both short and long term benefits. While the magnitude of the effect on non-cognitive skill is harder to quantify than that for cognitive skills, they should clearly not be neglected from a broader welfare perspective.

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Table 1A: Descriptive Statistics for year 1997

Variable	Obs.	Mean	Std. Dev.	Min	Max
Behavioral Problems Index	2077	5.632162	3.814646	0	15
Positive Behavior Scale	2741	3.281872	1.829813	0	5
Reading Standard Score	999	104.4074	15.9405	38	166
Mathematics Standard Score	1463	105.3739	17.70244	28	159
Body Mass Index	1390	18.35309	5.069856	2.8	62.7
Structured Activity Participation	2024	.3878458	.4873795	0	1
Sports Participation	2024	.3690711	.4826725	0	1
Lesson Participation	2024	.0296443	.1696458	0	1
Age	2774	5.908796	3.587047	1	13
Birth Order	2722	1.978325	1.096203	1	11
Low Birth Weight Indicator	2753	.127134	.3331836	0	1
Number of Siblings	2774	1.282624	1.062155	0	7
Female	2774	.4938717	.5000526	0	1
Mother School Dropout	2774	.1503244	.3574536	0	1
Mother High School Graduate	2774	.3759913	.4844651	0	1
Mother College Dropout	2774	.2548666	.4358648	0	1
Mother College Graduate	2774	.1701514	.3758335	0	1
Mother Education Missing	2774	.0486662	.215208	0	1
Father School Dropout	2774	.0930065	.2904939	0	1
Father High School Graduate	2774	.2454939	.4304572	0	1
Father College Dropout	2774	.1416727	.348777	0	1
Father College Graduate	2774	.1705119	.3761497	0	1
Father Education Missing	2774	.3493151	.4768396	0	1
Income-To-Needs Ratio	2774	3.742983	3.863925	0	49.69854
Mother Working	2774	.6229272	.4847408	0	1
Both Biological Parents	2774	.6733958	.4690557	0	1
Single Parent	2774	.2833453	.4507039	0	1
Step Parent	2774	.0356885	.1855459	0	1
No Biological Parent	2774	.0075703	.0866931	0	1
White	2767	.4741597	.4994221	0	1
African-American	2767	.4051319	.4910063	0	1
Hispanic	2767	.0751717	.2637158	0	1
Other Race	2767	.0455367	.2085157	0	1

Table 1B: Descriptive Statistics for year 2002

Variable	Obs.	Mean	Std. Dev.	Min	Max
Behavioral Problems Index	2077	5.651902	4.26299	0	17
Positive Behavior Scale	2741	4.137162	.593681	1	5
Reading Standard Score	999	101.017	16.56936	37	187
Mathematics Standard Score	1463	102.6671	16.29769	43	168
Body Mass Index	1390	23.22446	6.263165	10	60
Structured Activity Participation	2024	.3359684	.4724446	0	1
Sports Participation	2024	.3241107	.4681573	0	1
Lesson Participation	2024	.013834	.1168305	0	1
Age	2774	9.99279	3.71243	3	17
Birth Order	2722	1.978325	1.096203	1	11
Low Birth Weight Indicator	2753	.127134	.3331836	0	1
Number of Siblings	2774	1.322999	1.065573	0	8
Female	2774	.4938717	.5000526	0	1
Mother School Dropout	2774	.1272531	.3333163	0	1
Mother High School Graduate	2774	.3677001	.4822661	0	1
Mother College Dropout	2774	.2599135	.438666	0	1
Mother College Graduate	2774	.1737563	.3789681	0	1
Mother Education Missing	2774	.0713771	.2575001	0	1
Father School Dropout	2774	.0854362	.2795801	0	1
Father High School Graduate	2774	.2476568	.4317292	0	1
Father College Dropout	2774	.1373468	.3442751	0	1
Father College Graduate	2774	.1690699	.3748813	0	1
Father Education Missing	2774	.3604903	.4802293	0	1
Income-To-Needs Ratio	2774	5.203381	7.511671	0	176.7356
Mother Working	2774	.6914203	.4619905	0	1
Both Biological Parents	2774	.5976929	.4904516	0	1
Single Parent	2774	.3064167	.461088	0	1
Step Parent	2774	.0814708	.2736061	0	1
No Biological Parent	2774	.0144196	.1192343	0	1
White	2767	.4741597	.4994221	0	1
African-American	2767	.4051319	.4910063	0	1
Hispanic	2767	.0751717	.2637158	0	1
Other Race	2767	.0455367	.2085157	0	1

Table 2: Rates of Participation in Structured Activity, Lessons and Sports

Variable	Structured Activity		Lessons		Sports	
	1997	2002	1997	2002	1997	2002
Full Sample	.3878	.3359	.0296	.0138	.3691	.3241
White	.4466	.3694	.0422	.0223	.4191	.3505
African American	.3581	.2911	.0094	.0063	.3522	.288
Hispanic	.2486	.3005	.0116	0	.2428	.3005
Other Race	.3273	.3017	.0182	.0086	.3182	.3017
Mother School Dropout	.2853	.3135	.0061	.0033	.2791	.3102
Mother High School Grad	.3696	.2962	.0179	.008	.3589	.2916
Mother Some College	.4314	.3175	.0268	.0142	.413	.3049
Mother College Grad	.4528	.4468	.0533	.0331	.4237	.4184
Mother Working	.4137	.3264	.0283	.014	.3946	.3167
Income-Needs First Quartile	.3233	.2901	.01	.0116	.3183	.2843
Income-Needs Second Quartile	.3506	.29	.013	.0074	.3425	.2862
Income-Needs Third Quartile	.413	.309	.0325	.0139	.3902	.2969
Income-Needs Top Quartile	.5144	.4008	.0599	.0193	.4767	.384
Boy	.4609	.4124	.0163	.0083	.4524	.4075
Girl	.3214	.2479	.0376	.0191	.2954	.2321
Observations	2024	2024	2024	2024	2024	2024

Note: The change in the number of children that participated in structured activity between 1997 and 2002 is (896 – 795) = 101; the change in the number of children that participated in lessons between 1997 and 2002 is (61 – 33) = 28; the change in the number of children that participated in sports between 1997 and 2002 is (857 – 770) = 87.

Table 3: Main OLS Results for Structured Activity

Variable	BPI	Positive	Reading	Math	BMI
Structured Activity Participation	-0.529***	0.159***	0.353	2.173***	-0.876***
	(0.143)	(0.0372)	(0.734)	(0.599)	(0.221)
Age of Child	-0.0570***	0.175***	-0.572***	-0.186**	0.853***
	(0.0206)	(0.00516)	(0.131)	(0.0926)	(0.0363)
Birth Order	-0.00684	-0.123***	-0.698*	-0.264	0.0970
	(0.0874)	(0.0174)	(0.404)	(0.348)	(0.127)
Low Birth Weight	0.0947	0.0629	-1.378	-1.971*	-1.005**
	(0.246)	(0.0490)	(1.484)	(1.096)	(0.453)
Number of Siblings	0.00934	0.213***	-1.320***	-0.451	-0.533***
	(0.0878)	(0.0196)	(0.439)	(0.354)	(0.136)
Female	-0.862***	0.0656**	3.117***	-1.292*	-0.103
	(0.163)	(0.0332)	(0.824)	(0.682)	(0.273)
Mother High School Dropout	0.845**	-0.0892	-10.83***	-9.653***	0.539
	(0.354)	(0.0759)	(1.887)	(1.642)	(0.630)
Mother High School Grad	0.632**	-0.0263	-6.280***	-5.707***	0.653
	(0.258)	(0.0538)	(1.360)	(1.158)	(0.412)
Mother Some College	0.314	-0.0168	-2.896**	-2.474**	0.678*
	(0.246)	(0.0528)	(1.304)	(1.106)	(0.378)
Father High School Dropout	0.479	-0.0226	-4.996**	-6.524***	0.385
	(0.380)	(0.0823)	(1.978)	(1.817)	(0.769)
Father High School Grad	0.263	-0.0603	-4.512***	-5.683***	-0.136
	(0.273)	(0.0584)	(1.352)	(1.182)	(0.425)
Father Some College	0.291	-0.177***	-2.324	-4.100***	0.463
	(0.282)	(0.0613)	(1.514)	(1.257)	(0.458)
Income-Needs Ratio	-0.00574	0.000670	0.0316	0.0469	0.00687
	(0.0206)	(0.00326)	(0.0403)	(0.0489)	(0.0144)
Mother Working	-0.374**	0.147***	0.705	-0.115	0.193
	(0.165)	(0.0402)	(0.913)	(0.713)	(0.287)
Single Parent	0.851***	0.180***	-4.362***	-2.390*	-0.485
	(0.317)	(0.0658)	(1.358)	(1.278)	(0.446)
Step Parent	0.842**	0.148*	-7.404***	-3.889**	0.0895
	(0.418)	(0.0818)	(2.188)	(1.821)	(0.646)
No Biological Parent	2.861***	0.0295	-3.408	-5.930	0.655
	(0.979)	(0.183)	(8.059)	(3.750)	(1.245)
African-American	-0.417**	0.0532	-6.030***	-10.04***	1.838***
	(0.199)	(0.0424)	(1.127)	(0.926)	(0.346)
Hispanic	-1.273***	0.323***	-7.194	-10.24***	1.448**
	(0.327)	(0.0763)	(4.587)	(2.055)	(0.566)
Other Race	0.245	0.0571	-5.201	-4.795*	1.099
	(0.396)	(0.0817)	(3.704)	(2.765)	(0.790)
Observations	3372	4522	1796	2622	2380

Robust Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; Omitted Education Categories: Mother College Grad; Father College Grad

Table 4: Main OLS Results for Lesson Participation

Variable	BPI	Positive	Reading	Math	BMI
Lesson Participation	-0.0130	0.580***	2.549	3.801**	-0.817*
	(0.449)	(0.0816)	(2.665)	(1.835)	(0.469)
Age of Child	-0.0579***	0.177***	-0.564***	-0.170*	0.855***
	(0.0207)	(0.00514)	(0.131)	(0.0934)	(0.0365)
Birth Order	-0.0127	-0.123***	-0.693*	-0.258	0.0858
	(0.0875)	(0.0175)	(0.404)	(0.348)	(0.128)
Low Birth Weight	0.0944	0.0600	-1.347	-1.955*	-1.012**
	(0.247)	(0.0489)	(1.482)	(1.100)	(0.454)
Number of Siblings	-0.00328	0.218***	-1.305***	-0.392	-0.554***
	(0.0879)	(0.0196)	(0.435)	(0.354)	(0.136)
Female	-0.761***	0.0313	2.987***	-1.750**	0.0815
	(0.161)	(0.0325)	(0.824)	(0.694)	(0.272)
Mother High School Dropout	0.878**	-0.0849	-10.79***	-9.644***	0.568
	(0.355)	(0.0762)	(1.884)	(1.645)	(0.633)
Mother High School Grad	0.664**	-0.0218	-6.220***	-5.727***	0.678
	(0.259)	(0.0543)	(1.363)	(1.162)	(0.415)
Mother Some College	0.344	-0.0136	-2.857**	-2.513**	0.709*
	(0.246)	(0.0531)	(1.306)	(1.112)	(0.382)
Father High School Dropout	0.528	-0.0267	-4.997**	-6.797***	0.451
	(0.381)	(0.0825)	(1.988)	(1.826)	(0.775)
Father High School Grad	0.286	-0.0657	-4.532***	-5.792***	-0.104
	(0.274)	(0.0586)	(1.354)	(1.189)	(0.428)
Father Some College	0.284	-0.177***	-2.323	-4.065***	0.466
	(0.282)	(0.0617)	(1.515)	(1.264)	(0.461)
Income-Needs Ratio	-0.00685	0.000924	0.0319	0.0501	0.00522
	(0.0204)	(0.00325)	(0.0403)	(0.0491)	(0.0138)
Mother Working	-0.374**	0.149***	0.723	-0.137	0.158
	(0.165)	(0.0402)	(0.912)	(0.712)	(0.287)
Single Parent	0.881***	0.176***	-4.402***	-2.476**	-0.429
	(0.318)	(0.0658)	(1.360)	(1.258)	(0.448)
Step Parent	0.920**	0.130	-7.469***	-4.218**	0.192
	(0.417)	(0.0818)	(2.190)	(1.803)	(0.650)
No Biological Parent	2.820***	0.0488	-3.289	-5.576	0.572
	(0.978)	(0.183)	(8.072)	(3.753)	(1.255)
African-American	-0.374*	0.0512	-6.019***	-10.14***	1.904***
	(0.199)	(0.0423)	(1.117)	(0.924)	(0.348)
Hispanic	-1.223***	0.317***	-7.173	-10.38***	1.545***
	(0.328)	(0.0768)	(4.592)	(2.026)	(0.566)
Other Race	0.284	0.0548	-5.165	-4.728*	1.147
	(0.400)	(0.0829)	(3.703)	(2.793)	(0.784)
Observations	3372	4522	1796	2622	2380

Clustered Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Main OLS Results for Sports Participation

Variable	BPI	Positive	Reading	Math	BMI
Sports Participation	-0.532***	0.124***	-0.00618	1.886***	-0.818***
	(0.145)	(0.0377)	(0.735)	(0.602)	(0.223)
Age of Child	-0.0560***	0.175***	-0.575***	-0.190**	0.855***
	(0.0206)	(0.00519)	(0.131)	(0.0926)	(0.0363)
Birth Order	-0.00677	-0.123***	-0.695*	-0.262	0.0964
	(0.0874)	(0.0175)	(0.403)	(0.348)	(0.127)
Low Birth Weight	0.0922	0.0632	-1.362	-1.963*	-1.010**
	(0.246)	(0.0490)	(1.485)	(1.095)	(0.452)
Number of Siblings	0.0108	0.214***	-1.309***	-0.453	-0.531***
	(0.0879)	(0.0196)	(0.440)	(0.354)	(0.136)
Female	-0.871***	0.0620*	3.043***	-1.304*	-0.105
	(0.164)	(0.0334)	(0.825)	(0.683)	(0.274)
Mother High School Dropout	0.850**	-0.0926	-10.83***	-9.675***	0.542
	(0.354)	(0.0759)	(1.888)	(1.643)	(0.630)
Mother High School Grad	0.640**	-0.0295	-6.290***	-5.748***	0.664
	(0.258)	(0.0539)	(1.361)	(1.156)	(0.411)
Mother Some College	0.318	-0.0189	-2.908**	-2.493**	0.684*
	(0.246)	(0.0529)	(1.305)	(1.106)	(0.378)
Father High School Dropout	0.484	-0.0263	-5.042**	-6.591***	0.397
	(0.379)	(0.0822)	(1.981)	(1.818)	(0.769)
Father High School Grad	0.263	-0.0630	-4.524***	-5.685***	-0.135
	(0.273)	(0.0584)	(1.353)	(1.183)	(0.425)
Father Some College	0.293	-0.178***	-2.313	-4.099***	0.467
	(0.282)	(0.0614)	(1.515)	(1.256)	(0.459)
Income-Needs Ratio	-0.00591	0.000767	0.0322	0.0482	0.00649
	(0.0206)	(0.00328)	(0.0405)	(0.0493)	(0.0143)
Mother Working	-0.373**	0.147***	0.709	-0.121	0.193
	(0.165)	(0.0402)	(0.913)	(0.714)	(0.287)
Single Parent	0.851***	0.178***	-4.365***	-2.429*	-0.484
	(0.317)	(0.0656)	(1.355)	(1.280)	(0.447)
Step Parent	0.834**	0.145*	-7.448***	-3.954**	0.0794
	(0.418)	(0.0818)	(2.189)	(1.827)	(0.645)
No Biological Parent	2.866***	0.0302	-3.296	-5.941	0.658
	(0.978)	(0.183)	(8.066)	(3.751)	(1.246)
African-American	-0.412**	0.0489	-6.067***	-10.09***	1.851***
	(0.199)	(0.0424)	(1.126)	(0.926)	(0.346)
Hispanic	-1.267***	0.318***	-7.241	-10.29***	1.464***
	(0.327)	(0.0763)	(4.593)	(2.051)	(0.566)
Other Race	0.253	0.0522	-5.237	-4.849*	1.110
	(0.397)	(0.0818)	(3.709)	(2.768)	(0.790)
Observations	3372	4522	1796	2622	2380

Clustered Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Main FE Results for Structured Activity

Variable	BPI	Positive	Reading	Math	BMI
Structured Activity Participation	-0.272*	0.170***	-0.625	1.158*	-0.175
	(0.158)	(0.0646)	(0.824)	(0.701)	(0.263)
Age of Child	0.00921	0.218***	-0.934***	-0.469***	1.177***
	(0.0313)	(0.0131)	(0.172)	(0.138)	(0.0531)
Number of Siblings	0.0717	0.579***	0.391	1.504***	-0.235
	(0.122)	(0.0535)	(0.729)	(0.558)	(0.215)
Mother High School Dropout	-0.245	0.193	9.713	-2.359	0.586
	(0.872)	(0.342)	(11.08)	(5.240)	(1.813)
Mother High School Grad	0.103	0.582**	7.546	0.958	-0.907
	(0.596)	(0.260)	(8.411)	(2.883)	(1.098)
Mother Some College	-0.0938	0.306	3.651	-0.854	-1.787*
	(0.635)	(0.274)	(3.799)	(2.880)	(1.032)
Father High School Dropout	-2.312	-0.510	1.246	-4.105	0.172
	(2.160)	(0.515)	(3.000)	(5.209)	(1.347)
Father High School Grad	0.705	-0.0743	-3.463	-4.746*	-0.516
	(0.535)	(0.257)	(3.318)	(2.866)	(0.893)
Father Some College	0.577	-0.604	-14.18	-4.382	-1.725
	(0.918)	(0.378)	(10.41)	(5.700)	(1.392)
Income-Needs Ratio	0.00637	-0.0152	0.139*	-0.0269	-0.0363
	(0.0108)	(0.0635)	(0.0721)	(0.0444)	(0.0302)
Mother Working	-0.0951	0.218**	1.733	0.521	-0.395
	(0.201)	(0.0874)	(1.241)	(0.967)	(0.342)
Change in Family Structure	-0.194	-0.166*	0.488	-0.881	0.229
	(0.214)	(0.0883)	(1.126)	(0.931)	(0.339)
Observations	3372	4522	1796	2622	2380

Clustered Standard errors in parentheses;
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Main FE Results for Lesson Participation

Variable	BPI	Positive	Reading	Math	BMI
Lesson Participation	-0.0273	1.037***	2.091	4.058**	-0.160
	(0.505)	(0.152)	(2.791)	(1.756)	(0.882)
Age of Child	0.0129	0.219***	-0.899***	-0.457***	1.179***
	(0.0317)	(0.0130)	(0.176)	(0.139)	(0.0536)
Number of Siblings	0.0660	0.572***	0.360	1.497***	-0.236
	(0.122)	(0.0531)	(0.727)	(0.556)	(0.215)
Mother High School Dropout	-0.196	0.178	9.791	-2.503	0.612
	(0.878)	(0.343)	(11.13)	(5.218)	(1.811)
Mother High School Grad	0.165	0.557**	7.778	0.669	-0.870
	(0.590)	(0.262)	(8.388)	(2.882)	(1.097)
Mother Some College	-0.0767	0.295	3.763	-0.919	-1.789*
	(0.635)	(0.277)	(3.780)	(2.918)	(1.031)
Father High School Dropout	-2.351	-0.463	1.173	-3.837	0.140
	(2.156)	(0.512)	(2.957)	(5.185)	(1.316)
Father High School Grad	0.691	-0.0776	-3.451	-4.840*	-0.524
	(0.536)	(0.259)	(3.315)	(2.874)	(0.888)
Father Some College	0.557	-0.591	-14.40	-4.343	-1.770
	(0.919)	(0.385)	(10.35)	(5.693)	(1.390)
Income-Needs Ratio	0.00678	-0.0144	0.139*	-0.0262	-0.0363
	(0.0107)	(0.0621)	(0.0723)	(0.0444)	(0.0301)
Mother Working	-0.106	0.233***	1.735	0.581	-0.410
	(0.202)	(0.0871)	(1.251)	(0.970)	(0.344)
Change in Family Structure	-0.185	-0.167*	0.476	-0.986	0.237
	(0.216)	(0.0883)	(1.121)	(0.930)	(0.341)
Observations	3372	4522	1796	2622	2380

Clustered Standard errors in parentheses;
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Main FE Results for Sports Participation

Variable	BPI	Positive	Reading	Math	BMI
Sports Participation	-0.284*	0.0977	-0.866	0.751	-0.175
	(0.158)	(0.0650)	(0.822)	(0.705)	(0.261)
Age of Child	0.0105	0.216***	-0.935***	-0.480***	1.178***
	(0.0312)	(0.0131)	(0.172)	(0.137)	(0.0530)
Number of Siblings	0.0714	0.582***	0.393	1.508***	-0.235
	(0.122)	(0.0535)	(0.729)	(0.559)	(0.216)
Mother High School Dropout	-0.242	0.182	9.724	-2.452	0.592
	(0.872)	(0.343)	(11.07)	(5.234)	(1.813)
Mother High School Grad	0.104	0.567**	7.487	0.816	-0.904
	(0.596)	(0.261)	(8.410)	(2.881)	(1.099)
Mother Some College	-0.0925	0.298	3.633	-0.905	-1.785*
	(0.636)	(0.274)	(3.803)	(2.884)	(1.032)
Father High School Dropout	-2.309	-0.492	1.313	-4.023	0.174
	(2.161)	(0.514)	(3.014)	(5.193)	(1.348)
Father High School Grad	0.699	-0.0666	-3.469	-4.720*	-0.523
	(0.533)	(0.257)	(3.319)	(2.858)	(0.892)
Father Some College	0.573	-0.595	-14.09	-4.334	-1.729
	(0.918)	(0.381)	(10.42)	(5.701)	(1.391)
Income-Needs Ratio	0.00644	-0.0153	0.138*	-0.0274	-0.0363
	(0.0107)	(0.0640)	(0.0721)	(0.0445)	(0.0302)
Mother Working	-0.0957	0.220**	1.738	0.523	-0.396
	(0.201)	(0.0875)	(1.241)	(0.966)	(0.342)
Change in Family Structure	-0.198	-0.166*	0.472	-0.881	0.227
	(0.214)	(0.0884)	(1.127)	(0.933)	(0.340)
Observations	3372	4522	1796	2622	2380

Clustered Standard errors in parentheses;
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: FE Results for Structured Activity by Gender

Variable	BPI		Positive		Reading		Math		BMI	
	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
Structured Activity Participation	-0.216	-0.318	0.206**	0.146	-1.467	0.302	1.982**	0.290	-0.477	0.160
	(0.211)	(0.239)	(0.0871)	(0.0966)	(1.211)	(1.170)	(0.948)	(1.021)	(0.381)	(0.362)
Age of Child	0.000996	0.0234	0.210***	0.223***	-0.940***	-0.877***	-0.226	-0.738***	1.093***	1.275***
	(0.0450)	(0.0459)	(0.0184)	(0.0191)	(0.251)	(0.244)	(0.201)	(0.194)	(0.0774)	(0.0750)
Number of Siblings	0.0687	0.103	0.510***	0.663***	0.346	0.481	1.107	2.042**	-0.219	-0.213
	(0.163)	(0.183)	(0.0735)	(0.0751)	(1.029)	(1.005)	(0.738)	(0.861)	(0.223)	(0.405)
Mother High School Dropout	-0.320	-0.328	0.595	-0.199	9.820		-1.413	-6.897	2.693	-3.023
	(1.193)	(1.139)	(0.476)	(0.471)	(10.41)		(5.541)	(12.37)	(2.018)	(2.818)
Mother High School Grad	1.332	1.173*	0.686*	0.429	5.126	6.961	-1.024	2.244	1.502	-3.941***
	(0.914)	(0.688)	(0.377)	(0.356)	(4.615)	(5.198)	(4.612)	(3.695)	(1.434)	(1.517)
Mother Some College	1.199	1.680*	0.217	0.447	7.050	3.383	-2.994	4.282	-0.985	-2.687
	(0.821)	(0.866)	(0.372)	(0.426)	(4.407)	(7.156)	(4.135)	(4.188)	(1.216)	(1.644)
Father High School Dropout	-1.432	3.129**	-0.188	-0.689	-7.628***	1.463	-8.691	-2.473	0.215	0.714
	(1.807)	(1.497)	(0.701)	(0.698)	(2.631)	(3.505)	(7.953)	(6.444)	(2.688)	(1.525)
Father High School Grad	-0.129	2.103***	-0.204	0.0989	-4.090	-7.458	-3.904	-9.651	0.0572	-0.257
	(0.670)	(0.795)	(0.302)	(0.434)	(2.688)	(8.933)	(2.528)	(6.874)	(1.096)	(1.555)
Father Some College	0.779	1.119	-0.658	-0.601	0.864	-36.26*	3.518	-17.80	-2.874	-1.282
	(1.361)	(1.220)	(0.525)	(0.611)	(5.087)	(21.03)	(4.336)	(10.93)	(2.062)	(2.560)
Income-Needs Ratio	0.00386	0.00872	-0.0146	-0.0176	0.181**	-0.0366	-0.0491	0.0452	-0.0215	-0.109**
	(0.0111)	(0.0332)	(0.0684)	(0.0157)	(0.0815)	(0.179)	(0.0431)	(0.156)	(0.0332)	(0.0458)
Mother Working	0.191	-0.336	0.232*	0.211*	2.811*	0.448	2.217*	-1.710	-0.692	0.0115
	(0.278)	(0.295)	(0.120)	(0.128)	(1.500)	(1.931)	(1.340)	(1.346)	(0.440)	(0.513)
Change in Family Structure	-0.0917	-0.308	-0.130	-0.184	1.614	-1.784	-1.349	-1.020	0.390	0.159
	(0.299)	(0.308)	(0.121)	(0.129)	(1.611)	(1.447)	(1.310)	(1.300)	(0.442)	(0.517)
Observations	2065	2016	2361	2306	1601	1626	1891	1841	1798	1790

Robust Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: FE Results for Structured Activity by Race

Variable	BPI		Positive		Reading		Math		BMI	
	White	Afr-Amer	White	Afr-Amer	White	Afr-Amer	White	Afr-Amer	White	Afr-Amer
Structured Activity Participation	-0.285	-0.405	0.278***	0.0511	-0.375	-0.426	2.216**	0.712	-0.384	0.241
	(0.208)	(0.278)	(0.0887)	(0.108)	(1.160)	(1.223)	(0.970)	(1.043)	(0.301)	(0.489)
Age of Child	-0.0781*	0.154***	0.232***	0.199***	-0.951***	-1.140***	-0.346**	-0.656***	1.055***	1.420***
	(0.0402)	(0.0593)	(0.0169)	(0.0240)	(0.218)	(0.283)	(0.176)	(0.238)	(0.0604)	(0.107)
Number of Siblings	0.119	-0.0121	0.751***	0.382***	0.114	0.801	2.630***	1.064	0.207	-0.383
	(0.188)	(0.187)	(0.0790)	(0.0781)	(1.079)	(0.950)	(0.947)	(0.748)	(0.333)	(0.300)
Mother High School Dropout	-0.716	-0.382	-0.789	0.0626	7.32	5.969	-4.724	-1.640	-0.221	2.637
	(1.124)	(1.094)	(0.805)	(0.428)	(7.597)	(12.57)	(10.01)	(5.921)	(2.034)	(1.959)
Mother High School Grad	-1.510	0.907	-0.195	1.048***	13.90*	5.471	6.576	0.259	1.769	-1.524
	(1.190)	(0.705)	(0.534)	(0.287)	(7.180)	(4.019)	(6.070)	(2.999)	(1.955)	(1.329)
Mother Some College	-0.753	0.411	-0.197	0.536	4.757	2.507	2.273	-2.753	-0.187	-1.203
	(1.008)	(0.904)	(0.494)	(0.349)	(5.299)	(5.472)	(4.791)	(3.497)	(1.848)	(1.308)
Father High School Dropout	4.723***	1.154	1.391	-1.861***	4.049	-3.472	7.045	-13.63***	0.962	1.071
	(1.367)	(2.011)	(1.205)	(0.666)	(3.622)	(4.178)	(5.759)	(5.080)	(2.453)	(0.903)
Father High School Grad	2.059*	0.469	-0.219	-0.367	-11.59*	-1.374	-2.805	-5.538*	1.146	-1.466
	(1.235)	(0.602)	(0.492)	(0.329)	(6.973)	(3.016)	(5.908)	(3.329)	(1.107)	(1.056)
Father Some College	1.574	1.392	-0.448	-1.252	-23.16*	2.897	-2.072	-0.248	0.985	-5.036***
	(1.365)	(0.976)	(0.457)	(0.828)	(12.77)	(1.980)	(8.168)	(6.606)	(1.659)	(0.946)
Income-Needs Ratio	0.0194*	-0.0654	-0.0144	-0.0323	0.0877	1.299***	-0.0426	-0.00308	-0.0265	0.104
	(0.0105)	(0.0714)	(0.0631)	(0.0315)	(0.0770)	(0.352)	(0.0444)	(0.327)	(0.0307)	(0.109)
Mother Working	0.442*	-0.662**	0.0681	0.441***	2.226	1.376	1.306	-1.071	-0.647*	-0.0805
	(0.268)	(0.330)	(0.122)	(0.142)	(1.517)	(2.067)	(1.394)	(1.428)	(0.385)	(0.678)
Change in Family Structure	-0.123	-0.662*	-0.186	-0.134	0.993	0.271	-0.696	-1.108	0.549	-0.679
	(0.298)	(0.348)	(0.124)	(0.140)	(1.686)	(1.677)	(1.423)	(1.350)	(0.427)	(0.595)
Observations	2016	1585	2315	1796	1597	1325	1869	1527	1751	1428

Robust Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: FE Results for Lesson Participation by Gender

Variable	BPI		Positive		Reading		Math		BMI	
	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
Lesson Participation	0.190	-0.149	0.805***	1.128***	-8.628	4.253	3.631	4.335**	-0.656	0.0424
	(0.947)	(0.591)	(0.239)	(0.189)	(6.225)	(2.892)	(3.711)	(2.009)	(1.197)	(1.110)
Age of Child	0.00521	0.0256	0.209***	0.226***	-0.928***	-0.827***	-0.247	-0.693***	1.104***	1.273***
	(0.0447)	(0.0469)	(0.0183)	(0.0189)	(0.253)	(0.251)	(0.202)	(0.195)	(0.0764)	(0.0765)
Number of Siblings	0.0563	0.108	0.512***	0.647***	0.295	0.382	1.179	2.025**	-0.224	-0.214
	(0.163)	(0.182)	(0.0732)	(0.0742)	(1.023)	(1.004)	(0.743)	(0.846)	(0.225)	(0.407)
Mother High School Dropout	-0.252	-0.328	0.549	-0.178	10.17		-1.985	-6.674	2.792	-3.034
	(1.203)	(1.146)	(0.482)	(0.473)	(10.38)		(5.564)	(12.28)	(2.013)	(2.811)
Mother High School Grad	1.386	1.130*	0.642*	0.437	5.922	7.270	-1.718	2.418	1.659	-3.954
	(0.908)	(0.674)	(0.378)	(0.361)	(4.596)	(5.198)	(4.676)	(3.668)	(1.440)	(3.532)
Mother Some College	1.223	1.694**	0.169	0.489	7.912*	3.840	-3.532	4.688	-0.931	-2.682
	(0.826)	(0.850)	(0.370)	(0.437)	(4.525)	(7.184)	(4.189)	(4.252)	(1.240)	(1.650)
Father High School Dropout	-1.423	3.227**	-0.160	-0.633	-7.876***	1.760	-8.692	-2.325	0.199	0.764
	(1.826)	(1.425)	(0.701)	(0.694)	(2.633)	(3.399)	(7.842)	(6.445)	(2.548)	(1.551)
Father High School Grad	-0.149	2.118***	-0.183	0.0614	-4.162	-7.507	-3.792	-10.01	-0.0275	-0.272
	(0.677)	(0.787)	(0.304)	(0.438)	(2.661)	(8.989)	(2.484)	(6.937)	(1.059)	(1.565)
Father Some College	0.804	1.062	-0.656	-0.606	0.746	-36.07*	3.316	-18.02*	-2.913	-1.222
	(1.356)	(1.221)	(0.537)	(0.616)	(5.090)	(20.99)	(4.250)	(10.90)	(2.052)	(2.543)
Income-Needs Ratio	0.00406	0.00974	-0.0143	-0.0147	0.179**	-0.0321	-0.0485	0.0531	-0.0215	-0.109**
	(0.0110)	(0.0330)	(0.0689)	(0.0149)	(0.0813)	(0.181)	(0.0434)	(0.156)	(0.0326)	(0.0462)
Mother Working	0.180	-0.337	0.260**	0.210	2.347	0.456	2.352*	-1.707	-0.785*	0.00993
	(0.281)	(0.295)	(0.119)	(0.127)	(1.485)	(1.914)	(1.362)	(1.350)	(0.446)	(0.513)
Change in Family Structure	-0.0874	-0.291	-0.131	-0.185	1.686	-1.860	-1.433	-1.137	0.401	0.152
	(0.301)	(0.310)	(0.122)	(0.129)	(1.595)	(1.438)	(1.309)	(1.301)	(0.443)	(0.524)
Observations	2065	2016	2361	2306	1601	1626	1891	1841	1798	1790

Robust Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: FE Results for Lesson Participation by Race

Variable	**BPI**		**Positive**		**Reading**		**Math**		**BMI**	
	White	Afr-Amer	White	Afr-Amer	White	Afr-Amer	White	Afr-Amer	White	Afr-Amer
Lesson Participation	-0.524	2.135	1.225***	-0.0283	0.618	12.80**	4.541**	2.933	-0.445	0.268
	(0.505)	(1.772)	(0.167)	(0.283)	(3.102)	(5.282)	(1.987)	(4.063)	(1.056)	(1.361)
Age of Child	-0.0787*	0.162***	0.233***	0.198***	-0.930***	-1.133***	-0.339*	-0.658***	1.057***	1.417***
	(0.0411)	(0.0588)	(0.0167)	(0.0240)	(0.224)	(0.284)	(0.176)	(0.240)	(0.0605)	(0.108)
Number of Siblings	0.121	-0.0485	0.732***	0.383***	0.116	0.690	2.584***	1.055	0.216	-0.379
	(0.187)	(0.182)	(0.0776)	(0.0782)	(1.082)	(0.948)	(0.937)	(0.753)	(0.331)	(0.300)
Mother High School Dropout	-0.632	-0.260	-0.928	0.0593	7.12	6.363	-4.520	-1.729	-0.421	2.595
	(1.113)	(1.113)	(0.806)	(0.428)	(7.604)	(12.55)	(10.38)	(5.875)	(2.022)	(1.972)
Mother High School Grad	-1.425	1.028	-0.301	1.041***	13.97*	5.971	5.985	0.141	1.916	-1.524
	(1.181)	(0.685)	(0.544)	(0.286)	(7.141)	(3.995)	(6.111)	(2.992)	(1.989)	(1.340)
Mother Some College	-0.771	0.637	-0.239	0.522	4.645	3.539	2.427	-2.807	-0.244	-1.225
	(1.005)	(0.831)	(0.501)	(0.346)	(5.310)	(5.473)	(4.924)	(3.514)	(1.859)	(1.317)
Father High School Dropout	4.698***	1.010	1.433	-1.846***	4.158	-3.526	6.770	-13.16***	0.911	1.173
	(1.293)	(2.014)	(1.178)	(0.669)	(3.632)	(3.908)	(6.273)	(4.832)	(2.336)	(0.937)
Father High School Grad	2.108*	0.335	-0.232	-0.360	-11.58*	-1.580	-3.120	-5.607*	1.116	-1.460
	(1.226)	(0.583)	(0.496)	(0.331)	(6.960)	(2.955)	(5.867)	(3.347)	(1.122)	(1.072)
Father Some College	1.536	1.498	-0.385	-1.257	-23.30*	2.660	-1.471	-0.720	0.791	-5.100***
	(1.353)	(0.916)	(0.469)	(0.832)	(12.62)	(1.922)	(8.150)	(6.526)	(1.688)	(0.942)
Income-Needs Ratio	0.0193*	-0.0531	-0.0132	-0.0332	0.0868	1.361***	-0.0413	-0.00803	-0.0267	0.100
	(0.0105)	(0.0686)	(0.0613)	(0.0314)	(0.0771)	(0.341)	(0.0442)	(0.328)	(0.0303)	(0.111)
Mother Working	0.426	-0.695**	0.0975	0.442***	2.234	1.281	1.472	-1.092	-0.677*	-0.0662
	(0.270)	(0.332)	(0.121)	(0.142)	(1.528)	(2.068)	(1.402)	(1.427)	(0.390)	(0.683)
Change in Family Structure	-0.0937	-0.658*	-0.189	-0.133	1.014	0.392	-0.948	-1.123	0.591	-0.676
	(0.297)	(0.347)	(0.124)	(0.140)	(1.681)	(1.670)	(1.419)	(1.351)	(0.431)	(0.596)
Observations	2016	1585	2315	1796	1597	1325	1869	1527	1751	1428

Robust Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: FE Results for Sports Participation by Gender

Variable	BPI		Positive		Reading		Math		BMI	
	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
Sports Participation	-0.235 (0.207)	-0.329 (0.243)	0.194** (0.0870)	-0.000242 (0.0981)	-1.404 (1.192)	-0.209 (1.187)	1.697* (0.946)	-0.322 (1.040)	-0.460 (0.377)	0.152 (0.366)
Age of Child	0.000964 (0.0449)	0.0260 (0.0457)	0.210*** (0.0184)	0.221*** (0.0190)	-0.936*** (0.252)	-0.887*** (0.243)	-0.235 (0.202)	-0.749*** (0.192)	1.095*** (0.0771)	1.273*** (0.0755)
Number of Siblings	0.0678 (0.164)	0.104 (0.183)	0.512*** (0.0735)	0.662*** (0.0749)	0.337 (1.027)	0.458 (1.003)	1.129 (0.738)	2.016** (0.863)	-0.222 (0.223)	-0.215 (0.406)
Mother High School Dropout	-0.325 (1.192)	0.315 (1.139)	0.593 (0.477)	-0.217 (0.472)	9.841 (10.42)		-1.494 (5.540)	-6.935 (12.35)	2.702 (2.018)	-3.038 (2.822)
Mother High School Grad	1.328 (0.914)	1.167* (0.688)	0.684* (0.377)	0.395 (0.357)	5.159 (4.614)	6.841 (5.202)	-1.124 (4.619)	2.056 (3.668)	1.511 (1.435)	-3.946 (3.519)
Mother Some College	1.197 (0.821)	1.676* (0.867)	0.216 (0.372)	0.435 (0.430)	7.065 (4.408)	3.323 (7.177)	-3.056 (4.139)	4.272 (4.179)	-0.982 (1.217)	-2.691 (1.645)
Father High School Dropout	-1.431 (1.806)	3.129** (1.500)	-0.187 (0.701)	-0.632 (0.693)	-7.597*** (2.626)	1.619 (3.529)	-8.717 (7.907)	-2.311 (6.418)	0.224 (2.680)	0.716 (1.523)
Father High School Grad	-0.129 (0.670)	2.080*** (0.786)	-0.202 (0.302)	0.108 (0.435)	-4.102 (2.686)	-7.608 (8.974)	-3.881 (2.519)	-9.750 (6.873)	0.0518 (1.095)	-0.239 (1.563)
Father Some College	0.776 (1.362)	1.102 (1.217)	-0.658 (0.526)	-0.574 (0.618)	0.829 (5.087)	-36.04* (21.15)	3.505 (4.322)	-17.72 (10.95)	-2.882 (2.060)	-1.264 (2.555)
Income-Needs Ratio	0.00383 (0.0111)	0.00936 (0.0331)	-0.0147 (0.0686)	-0.0184 (0.0156)	0.181** (0.0816)	-0.0408 (0.178)	-0.0494 (0.0432)	0.0429 (0.156)	-0.0217 (0.0333)	-0.109** (0.0459)
Mother Working	0.195 (0.278)	-0.344 (0.295)	0.230* (0.120)	0.214* (0.128)	2.799* (1.499)	0.423 (1.934)	2.204 (1.342)	-1.729 (1.340)	-0.692 (0.440)	0.0137 (0.514)
Change in Family Structure	-0.0918 (0.299)	-0.317 (0.308)	-0.131 (0.121)	-0.184 (0.130)	1.624 (1.609)	-1.790 (1.447)	-1.354 (1.310)	-1.046 (1.301)	0.393 (0.442)	0.163 (0.521)
Observations	2065	2016	2361	2306	1601	1626	1891	1841	1798	1790

Robust Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14: FE Results for Sports Participation by Race

Variable	BPI		Positive		Reading		Math		BMI	
	White	Afr-Amer	White	Afr-Amer	White	Afr-Amer	White	Afr-Amer	White	Afr-Amer
Sports Participation	-0.254	-0.469*	0.143	0.0554	-0.558	-0.793	1.458	0.630	-0.326	0.202
	(0.208)	(0.273)	(0.0899)	(0.109)	(1.155)	(1.224)	(0.971)	(1.055)	(0.290)	(0.502)
Age of Child	-0.0756*	0.154***	0.229***	0.199***	-0.951***	-1.145***	-0.375**	-0.658***	1.060***	1.419***
	(0.0400)	(0.0592)	(0.0168)	(0.0240)	(0.218)	(0.283)	(0.174)	(0.238)	(0.0609)	(0.107)
Number of Siblings	0.120	-0.0122	0.753***	0.382***	0.108	0.815	2.601***	1.070	0.215	-0.381
	(0.188)	(0.187)	(0.0791)	(0.0781)	(1.079)	(0.949)	(0.951)	(0.748)	(0.337)	(0.300)
Mother High School Dropout	-0.692	-0.393	-0.856	0.0627	7.44	5.920	-4.724	-1.655	-0.229	2.627
	(1.122)	(1.091)	(0.806)	(0.428)	(7.602)	(12.56)	(10.13)	(5.919)	(2.028)	(1.961)
Mother High School Grad	-1.493	0.900	-0.239	1.049***	13.85*	5.401	6.354	0.232	1.809	-1.528
	(1.189)	(0.707)	(0.540)	(0.287)	(7.182)	(4.016)	(6.073)	(2.998)	(1.966)	(1.331)
Mother Some College	-0.752	0.393	-0.198	0.537	4.799	2.408	2.362	-2.779	-0.186	-1.213
	(1.008)	(0.905)	(0.498)	(0.349)	(5.311)	(5.473)	(4.801)	(3.498)	(1.842)	(1.307)
Father High School Dropout	4.711***	1.177	1.403	-1.862***	4.023	-3.260	6.885	-13.57***	0.974	1.088
	(1.359)	(2.008)	(1.188)	(0.665)	(3.614)	(4.267)	(5.925)	(5.051)	(2.436)	(0.909)
Father High School Grad	2.069*	0.455	-0.232	-0.366	-11.58*	-1.362	-2.963	-5.503*	1.150	-1.448
	(1.234)	(0.593)	(0.493)	(0.329)	(6.980)	(3.036)	(5.887)	(3.321)	(1.108)	(1.064)
Father Some College	1.573	1.343	-0.423	-1.251	-23.08*	2.899	-1.920	-0.266	0.963	-5.033***
	(1.364)	(0.973)	(0.463)	(0.828)	(12.79)	(1.982)	(8.174)	(6.601)	(1.663)	(0.955)
Income-Needs Ratio	0.0194*	-0.0661	-0.0144	-0.0323	0.0876	1.294***	-0.0419	-0.00445	-0.0267	0.104
	(0.0105)	(0.0710)	(0.0638)	(0.0315)	(0.0770)	(0.352)	(0.0446)	(0.327)	(0.0306)	(0.109)
Mother Working	0.441*	-0.665**	0.0693	0.441***	2.229	1.395	1.306	-1.072	-0.650*	-0.0748
	(0.268)	(0.330)	(0.122)	(0.142)	(1.517)	(2.066)	(1.391)	(1.428)	(0.386)	(0.678)
Change in Family Structure	-0.122	-0.665*	-0.193	-0.133	0.968	0.274	-0.733	-1.104	0.554	-0.678
	(0.298)	(0.347)	(0.124)	(0.140)	(1.687)	(1.676)	(1.425)	(1.351)	(0.433)	(0.596)
Observations	2016	1585	2315	1796	1597	1325	1869	1527	1751	1428

Robust Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Essay 2

Maternal Employment and Non-Cognitive Skill Formation:

Evidence from NLSY79

Günther Fink[16] **Sumanta Mukherjee**

Harvard School of Public Health **University of Kansas**

[16] Department of Global Health and Population, Harvard School of Public Health, 665 Huntington Avenue, Building 1, Room 1110, Boston, MA 02115. (email: gfink@hsph.harvard.edu)

1. INTRODUCTION

While cognitive skill formation among children has been subject to wide academic scrutiny, the impediments to a child's non-cognitive development have received comparatively scant attention. The literature on investments in children has traditionally focused on standardized tests scores (such as the PIAT Math and Reading), with very little emphasis on non-cognitive outcomes.[17] The recent literature on human capital however argues that in addition to cognitive skills (as measured by test scores), a variety of non-cognitive skills are also very important determinants of subsequent socioeconomic success (Heckman and Krueger, 2004). The study challenges the conventional point of view that equates skill with intelligence, adding that "numerous instances can be cited of people with high IQs who fail to achieve success in life because they lacked self-discipline and of people with low IQs who succeeded by virtue of persistence, reliability and self-discipline". This research therefore cites social skills, motivation and other non-cognitive skills (in addition to basic intelligence) as key to labor market success. Heckman's concern is reflected in a small but growing literature that attempts to identify the proximate factors that determine or at least influence the development of adolescents' non-cognitive skills.[18]

The various processes that shape children's non-cognitive skills are however not fully understood. In this essay, I concentrate on one observable phenomenon that could potentially influence the process of skill formation in children. In particular, I use the first eleven waves of the NLSY-Child data to examine how maternal employment affects non-cognitive development in children.

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[17] Bernal and Keane (2006) surveys a large literature on child outcomes (particularly as a consequence of maternal employment). The survey reveals the strong bias in favor of test scores as the primary measure of child outcomes.

[18] Aizer (2004) is an important example.

In the following subsections, I describe the existing literature, outline the data and the methodology, and present some preliminary results.

2. EVIDENCE ON MATERNAL EMPLOYMENT AND CHILD OUTCOMES

An extensive literature analyzes the impact of parental resources on a variety of child outcomes. Korenman *et. al*. (1995), for example, uses NLSY data to show that an increase in current income (1993 dollars) by $10,000 is associated with a small increase in outcome variables measuring cognitive development and behavioral problems. A similar increase in permanent income has a somewhat larger positive effect on both reading ability and behavioral problems.[19] Blau (1999) uses the EITC expansion of 1993 to examine the impact of a permanent increase in income on child outcomes for the NLSY-Child 1979 cohort. He finds that a (nominal) increase in maximum credit from $953 to $2040, viewed as a permanent increase in income, leads to an increase of at most 1 to 1.5 percent of a standard deviation of the various child outcomes analyzed therein. He concludes that family income (current and permanent) has a negligible impact on child development; family background plays a more vital role in determining child outcomes.

Shea (2000) uses variations in parental 'luck' factors (such as job loss experience) to establish a causal impact of parental income on child outcomes. Echoing the results in the existing literature, he finds a negligible impact of changes in parental income on children's human capital acquisition.[20] Dahl and Lochner (2005) utilize the large expansion in EITC to estimate the causal effect of income on children's math and reading achievement. Using a fixed-

[19] The largest impact of a $10,000 increase in permanent income is 23.5 percent of a standard deviation in reading ability. With fewer controls, the largest effect is a 35.8 percent of a standard deviation improvement in behavioral problems. The effect of a $10,000 increase in income averages 21.6 percent of a standard deviation of the dependent variable across five different outcomes, when income is initially less than half the poverty line, but averages 7.0 percent of a standard deviation beginning from an income level between 1.85 and three times the poverty line.

[20] The results of Shea (2000) however indicate that parental income does matter in a sample of low-income households.

effects instrumental variables strategy they find that a $1,000 increase in income raises math test scores by 2.1 percent and reading test scores by 3.6 percent of a standard deviation. The results are stronger for children from families that are affected most by the EITC expansion.

The research cited here allows us to draw some broad conclusions regarding household incomes and child outcomes. Researchers have consistently found that increases in income have a minor effect on child outcomes. The EITC expansions, by providing generous tax breaks, created an alternative natural experiment setting to test the income effect hypothesis; however the results have still remained surprisingly similar.

A concurrent strand of scholarly work attempts to investigate the importance of the parental employment in child development.[21] Much of the past research on this question has concentrated on the availability of parental time input in the first three years of the child. The primary motivation for concentrating on the first few years is derived from the developmental psychology literature, which emphasizes the effect of early influences on brain development (Blau and Grossberg, 1992).

The other important characteristic of this literature is the widespread use of some measure of a child's cognitive ability as the primary outcome variable. Cognitive development is typically captured by standardized (or raw) test scores of children of different age groups. A variety of recent research in this field finds that maternal employment during the first year of the child's life has a deleterious effect, while that in the second or third years has none or some offsetting positive impact (Waldfogel *et. al.*, 2002; Neidell, 2000). James-Burdumy (2005) uses fixed-effects in determining the effect of maternal employment on child cognitive outcomes (as

[21] In the absence of detailed time use data, parental employment has often been used as a proxy for the time input in child development (Bernal and Keane 2006).

measured by PPVT, PIAT Math and PIAT Reading scores) in the first three years of the child's life. In particular, she uses a GMM technique to estimate child and mother fixed-effects regressions. She finds that the PIAT Math and Reading scores were negatively affected by maternal employment in the first year. None of the test scores were affected by maternal employment in the second year. Finally, work in the third year positively affected PIAT Math scores. Ruhm (2004) finds that adding a more complete set of controls leads to a much stronger negative impact of maternal employment in the first three years of the child's life.[22]

In addition to test scores, measures of a child's non-cognitive development have recently been cited as being important determinants of subsequent labor market success (Heckman *et. al.*, 2004). Yet, very little research has analyzed the importance of maternal inputs on non-cognitive development, especially for school-aged children. Aizer (2004) provides an important exception. She estimates a fixed-effect linear probability model to determine the impact of child supervision after school on the probability of risky behavior (skipping school, getting drunk/high, stealing something and hurting someone). The key explanatory variable is an indicator of whether there is usually an adult present when the child returns from school.[23] The results indicate a lower probability of risky behavior for children monitored by any adult after school. While this research provides an interesting analysis of the determinants of non-cognitive development among school-age children, it does not connect maternal employment (or unemployment) spells with such outcomes. By using a single indicator variable for child supervision (which includes

[22] Indeed there is some literature that finds a completely negative effect of maternal employment for all three years of the child (Han *et. al*. 2001, Harvey 1999). Liu, Mroz and van der Klaauw (forthcoming) estimate a structural model of mothers' employment, migration (and hence school) choice, and child outcomes. They also find a negative effect of maternal employment on the cognitive development of children aged 5-15. Bernal (2005) estimates a structural model of employment for married mothers and finds significant negative effects on cognitive achievement of children aged 3-7 years.

[23] Children who reported going to day care, or an after-school program, or the home of a relative were considered as being supervised.

post-school monitoring by any adult or day-care), it potentially misses some interesting effects of the mother’s labor market dynamics on child development.

My research is distinguished from existing scholarly work in two ways. First, this paper complements the large literature on very young children by focusing attention on school-age children. In particular I look at the cognitive outcomes for children aged five through eighteen. The cognitive outcomes are measured by scores on Peabody Individual Achievement Tests of Mathematics (PIAT Math) and Reading Comprehension (PIAT Read) measuring academic achievement of children aged five or older. Second, I investigate the impact of maternal employment on non-cognitive outcomes as well. In particular, I assess the effect of maternal employment on Aizer’s index of risky behavior. In addition, I use the Behavioral Problems Index (BPI) measuring the frequency, range and type of behavior problems of children aged four and over, as an indicator of a child’s emotional development.

3. EMPIRICAL FRAMEWORK

In this essay, I examine the impact of the maternal employment on the cognitive and non-cognitive outcomes of children using mother-child matched data from the first eleven waves of the NLSY-Child sample (1986 through 2006). I specify a variety of child outcomes as linear functions of parental resources and a vector of controls in the following form:

$$y_{jt} = X_{jt}\alpha + \beta E_{jt} + \gamma H_{jt} + \varepsilon_{jt} \qquad (1),$$

where y_{jt} is the *j*th child's outcome in year *t*, *E* measures the fraction of weeks mother was employed since last interview (maternal work at the 'extensive' margin), *H* represents the number of hours worked per week (as a measure of the 'intensive' margin of employment), *X* is a vector of controls, ε is the error term, and α, β and γ are parameters. The basic models are estimated by ordinary least squares (OLS) with clustered standard errors.

To account for the potential unobservable heterogeneity, I employ a mother fixed-effect to control for unobserved time-invariant factors (such as genetic or environmental influences) specific to the mother and the household. The fixed-effect model is robust to the endogeneity of any explanatory variables provided that the fixed effect is the only source of correlation between the regressors and the error term. The mother fixed-effect model for the *i*th family is specified as follows:

$$y_{ijt} = X_{ijt}\alpha + \beta E_{ijt} + \gamma H_{ijt} + \theta_{ij} + \varepsilon_{ijt} \qquad (2),$$

where θ_{ij} represents the mother fixed-effect for the *i*th mother or family. The error term can be decomposed into three components: $\varepsilon_{ijt} = \varphi_i + \eta_j + \upsilon_{ijt}$, where φ and η represent the family-specific and individual-specific effects respectively. Assuming that unobservable maternal traits are sibling-invariant ($\theta_{ij} = \theta_i$), and operate only through the family-specific effect φ, one can take first-differences with respect to families to obtain:

$$\Delta y_{ij} = \alpha\Delta X_{ij} + \beta\Delta E_{ij} + \gamma\Delta H_{ij} + \Delta\varepsilon_{ij} \qquad (3).$$

First differencing within families therefore eliminates any observed or unobserved variables that do not vary (over time) within a family. The model is identified under the assumption that the differences in exposure to maternal employment across siblings are exogenous to the children's development.

4. DATA AND DESCRIPTIVE STATISTICS

The National Longitudinal Survey of the Youth has regularly interviewed a national sample of individuals who were aged 14 to 21 as of December 31, 1978. The sample over-represents Blacks, Hispanics, low-income Whites and military personnel. In each even numbered year since 1986, the children born to the female participants of the NLSY sample have been administered a set of assessments of cognitive, social, emotional and physical development together with the quality of home environment. The data used in the paper are from the first eleven waves of the NLSY Child files collected over the period 1986 to 2006. My sample includes mother-child matched data for children in their school years (i.e. aged about five through eighteen) for whom measures of cognitive and non-cognitive development are available. The particular choice of age group reflects the hypothesis that non-cognitive skill acquisition is most affected by parental time in this age interval.

The primary outcome variables in the second essay are measures of cognitive and non-cognitive development of children. The cognitive outcomes are captured by the scores on the Peabody Individual Assessment Tests of Mathematics (PIATMATH) and Reading Recognition (PIATREAD) that indicate academic achievement for children aged five and above. Following Aizer (2004), I use her index of antisocial or risky child behavior as a measure of the child's non-cognitive development. The index is based on the following specific behaviors: skipping school, getting drunk/high, stealing something and hurting someone bad enough to need a doctor. In addition, the lack of maternal time could lead to nontrivial emotional problems for children and adolescents. Therefore I use the Behavioral Problems Index (BPI) measuring the frequency, range and type of behavior problems of children aged four and over, as an indicator of a child's emotional development.

The two primary explanatory variables measure the mothers' labor market commitments. First, I use the fraction of weeks worked since last interview as a measure of maternal work at the extensive margin. Second, I use the hours of work per week worked as a measure of work at the intensive margin.

A variety of supplementary 'home' inputs tend to influence a child's development. The 'Home Inventory' variables reported in the NLSY79 are used to summarize the quantity and quality of these supplementary inputs available in the child's home. This measure is derived from a series of child-age-specific questions and interviewer observations on the home environment and the nature of mother-child interactions. In addition, I use a number of core maternal background regressors that are intended to capture the education, demographic characteristics, income and location of the mother.[24]

Along with income, a household's size can often determine the amount of care (specifically, time) allocated to an individual child. In some cases, the birth order and gender of an individual child influences his/her outcomes. Race can often play a significant role in determining the nature and extent of family ties and informal child supervision possibilities. Therefore I add some other controls that capture the child's gender, race, birth order and number of siblings. Finally I also incorporate an indicator for the child's living arrangement, which is equal to 1 if the child stays with the mother and 0 otherwise. Table 1 outlines the descriptive statistics for the variables used in this essay.

[24] For mother's education, we use information on the highest grade completed by mother. I have not included mothers' AFQT test results because there is little consensus in the literature on what the score really measures.

5. RESULTS

The main regression results for four different outcome variables are presented in Tables 2 to 4. Tables 2 and 3 present estimates of the effect of maternal employment on PIAT Math and Reading scores. The OLS results in both tables indicate a strong impact of maternal work (on both the 'extensive' and 'intensive' margins) on cognitive achievement. However the effect ceases to be significant when I use mother fixed-effects. The basic positive correlation appears to be mostly driven by mother and household-specific factors that are positively correlated with both income and employment and thus generate a classical omitted variable bias in the OLS estimates. Even with household fixed effects, however, the measure of home inputs turns out a highly significant determinant of child's cognitive outcomes and is robust to changes in specification or sample. These results strongly highlight the importance of home environment on a child's cognitive development. The results reported in Tables 2 (Math) and 3 (Reading and Comprehension) look overall very similar. Overall maternal employment appears to be slightly more detrimental for boys (column 3 of Tables 2 and 3), even though the estimate is significantly different from zero only for the reading and comprehension score.

Table 4 presents estimates of the effect of maternal employment on a child's emotional well-being as reflected by the BPI score. While the OLS results do not show significant results, all the specifications with mother fixed-effects indicate that maternal employment at the 'extensive' margin has a highly significant effect on behavioral problems. In particular, it appears that a larger number of weeks of employment for a mother significantly exacerbated behavioral problems for her children. These results appear to be very robust across sampling strata; the magnitudes and significance of the coefficients change very little when I restrict the sample to boys (column 3), African Americans (column 4) or Hispanics (column 5). The number of hours worked per week, on the other hand, has little impact on the BPI score. Home inputs turn out to be important determinants of a child's emotional well-being, with a higher quality of home environment significantly reducing behavioral problems. Two other interesting points emerge. In all the specifications, first and second born children do much better than their younger siblings in dealing with behavioral problems. Finally, girls fare significantly better than boys on BPI score across all specifications and samples.

In Table 5, we test the effect of maternal employment on a behavioral problem index suggested by Aizer (2004). The dependent variable is an indicator, which is coded to 1 if the child has either stolen, skipped school, got drunk or hurt anybody. The results are mixed, and somewhat difficult to interpret. The OLS results imply that more participation in the labor market is associated with lower behavioral problems. This effect disappears in the full sample once I control for mother fixed effects. It does, however, persist in the male sample. The interpretation of this finding is not straightforward. Given the self-reported nature of the behavioral problems index, one might argue that boys with working mothers tend to report less of their bad deeds.

Our results suggest that the effect of maternal labor force participation on children's non-cognitive development is sensitive to the measurement of behavioral problems. While behavioral problems as measured by the BPI are exacerbated by maternal employment, (male) children score lower on the Aizer index if their mothers work for more weeks in a year. To reconcile these results, we estimated the correlation between the two indexes of behavioral problems. The correlation between BPI and Aizer index is 0.16 in our data. We therefore emphasize that the two measures really are quite different, which explains the weak correlation between them. Indeed, as noted above, Aizer's index is constructed on self-reports of 10-14 year old children regarding actual events that indicate behavioral problems. The BPI, on the other hand, is calculated using six subscales; it is not based on self-reports; and finally it is applicable to the age group 5-18.

6. CONCLUDING REMARKS

With rapidly increasing female labor force participation over the last few decades, a lot of research has been dedicated to identifying the causal effect of maternal work during early childhood on subsequent child development; relatively less attention has been given to the effect of maternal employment during the later stages of childhood (as well as early adulthood). In this essay, I have used longitudinal data from the US to test whether a mother's attachment to the labor market during the ages 5-18 significantly affects a child's cognitive and non-cognitive development. While we find that maternal employment has no effect on the cognitive development of children, we find a strong and highly significant relationship between maternal employment and the frequency and severity of children's behavioral and psychological problems as summarized in the Behavioral Problems Index (BPI). This effect appears to be consistent across gender and race.

The results in this paper not only highlight the important impact maternal employment during childhood and early adulthood may have on child development; they also underline the very differential effects parental choices may have on the psychological and mental well being of their children. While parental employment is likely to have only an indirect positive effect on children's school performance, it appears to have a rather important negative effect on the child's emotional well being. Even though the magnitude of these effects may be harder to quantify than the consequences of poor performance in school, they should clearly not be neglected from a broader welfare perspective.

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Table 1: Descriptive Statistics from NLSY-Child 1979

Variable	*Mean*	*Std. Dev.*	*Min*	*Max*
PIAT Math	100.20	13.91	0	135
PIAT Reading	101.18	13.86	19	135
Behavioral Problems Index	64.23	62.39	0	280
Aizer Index	0.32	0.47	0	1
Age	9.57	2.81	4.916667	18.08333
Age mother	33.99	5.08	21	47
African American	0.30	0.46	0	1
Hispanic	0.20	0.40	0	1
Lives with mother	0.98	0.14	0	1
Number of siblings	2.61	1.19	0	9
Home inventory score	974	157	80	1333
Mother education	12.57	2.31	0	20
Family income	43633	68783	0	974100
Urban area	0.75	0.44	0	1
Mother married	0.62	0.49	0	1
Fraction employed	0.63	0.43	0	1

Note: Number of unique children in the sample is 8205. Number of unique mothers in the sample is 3749. The total number of observations is 22894.

Table 2: PIAT Math Scores and labor market participation

Dependent Variable	**Standardized PIAT Math Score**				
	(1)	(2)	(3)	(4)	(5)
Fraction of Year Employed	1.288***	-0.0464	-0.270	0.0454	0.630
	(0.45)	(0.43)	(0.60)	(0.77)	(0.93)
Average Hours Per Week	-0.0440***	-0.0109	-0.0000362	-0.0213	-0.0324*
	(0.010)	(0.0095)	(0.013)	(0.018)	(0.020)
Number of Siblings	-0.504***	-0.296	-0.300	-0.340	-0.698
	(0.17)	(0.25)	(0.41)	(0.39)	(0.49)
Home Inventory Score	0.0115***	0.00494***	0.00424***	0.00576***	0.00307
	(0.00098)	(0.00092)	(0.0013)	(0.0015)	(0.0020)
Black	-5.987***				
	(0.40)				
Hispanic	-4.286***				
	(0.43)				
Married	0.0743	0.0428	-0.0290	-0.688	0.550
	(0.34)	(0.39)	(0.58)	(0.61)	(1.01)
Female	-0.143				
	(0.26)				
Family Income	0.0000132***	-0.000000534	-0.00000161	0.00000294	-0.00000430
	(0.0000024)	(0.0000018)	(0.0000024)	(0.0000039)	(0.0000035)
Lives with Mother	-0.402	-1.279	-1.166	-1.072	-0.700
	(0.90)	(0.93)	(1.26)	(1.87)	(3.10)
Mother's Education	1.198***	0.00680	0.109	-0.388	0.0114
	(0.079)	(0.22)	(0.30)	(0.42)	(0.48)
Urban	0.300	-0.697**	-0.585	0.540	-1.360
	(0.32)	(0.34)	(0.47)	(0.78)	(0.90)
Constant	77.16***	101.1***	102.3***	102.6***	105.4***
	(3.97)	(3.69)	(5.04)	(7.95)	(8.49)
Sample	All	All	Boys only	Black	Hispanic
Specification	OLS	FE	FE	FE	FE
Observations	17468	17468	8755	5134	3355

Robust standard errors in parentheses are clustered at the family level.
*** p<0.01, ** p<0.05, * p<0.1

All specifications control for sex, birth order, ethnicity, living with mother, mother's marital status and education, and urban residence.

Table 3: PIAT Reading Comprehension Score and Labor Market Participation

Dependent Variable	Standardized PIAT Reading and Comprehension Score				
	(1)	(2)	(3)	(4)	(5)
Fraction of Year Employed	1.704***	0.0267	-1.201*	0.428	-0.240
	(0.44)	(0.46)	(0.65)	(0.80)	(0.99)
Average Hours Per Week	-0.0451***	-0.0131	-0.00688	-0.0163	-0.00785
	(0.010)	(0.010)	(0.016)	(0.021)	(0.026)
Number of Siblings	-0.546***	-0.183	0.194	-0.354	-0.377
	(0.16)	(0.26)	(0.36)	(0.42)	(0.63)
Home Inventory Score	0.0114***	0.00434***	0.00301**	0.00468***	0.00276
	(0.0010)	(0.0010)	(0.0015)	(0.0016)	(0.0023)
Black	-4.301***				
	(0.40)				
Hispanic	-1.833***				
	(0.42)				
Married	0.176	-0.0641	0.282	-0.182	0.0494
	(0.33)	(0.42)	(0.63)	(0.66)	(1.10)
Female	1.358***				
	(0.26)				
Family Income	0.00000804***	0.00000338*	0.000000245	0.00000267	0.00000594
	(0.0000021)	(0.0000019)	(0.0000025)	(0.0000050)	(0.0000061)
Lives with Mother	-1.130	-0.595	-0.931	1.440	-1.568
	(0.92)	(0.90)	(1.37)	(1.76)	(2.56)
Mother's Education	0.968***	0.289	0.367	0.0781	0.247
	(0.075)	(0.23)	(0.32)	(0.48)	(0.41)
Urban	0.449	-0.673*	-0.346	-0.186	0.319
	(0.32)	(0.39)	(0.54)	(0.78)	(1.03)
Constant	75.52***	89.82***	83.36***	113.8***	92.44***
	(2.30)	(3.81)	(6.59)	(6.86)	(7.23)
Sample	All	All	Boys only	Black	Hispanic
Specification	OLS	FE	FE	FE	FE
Observations	14828	14828	7330	4432	2811

Robust standard errors in parentheses are clustered at the family level.
*** p<0.01, ** p<0.05, * p<0.1

All specifications control for sex, birth order, ethnicity, living with mother, mother's marital status and education, and urban residence.

Table 4: Behavior Problems Index (BPI) and Labor Market Participation

Dependent Variable	Behavioral Problems Index (BPI) Raw Score				
	(1)	(2)	(3)	(4)	(5)
Fraction of Year Employed	2.658	12.18***	13.13***	13.48***	12.27**
	(2.50)	(2.56)	(3.49)	(4.71)	(5.69)
Average Hours Per Week	0.00496	-0.0820	-0.118	-0.0762	-0.227*
	(0.054)	(0.055)	(0.078)	(0.11)	(0.12)
Number of Siblings	-2.576***	4.468***	4.117**	4.537*	7.238***
	(0.83)	(1.25)	(1.73)	(2.39)	(2.36)
Home Inventory Score	-0.0846***	-0.0347***	-0.0219***	-0.0337***	-0.0387***
	(0.0052)	(0.0052)	(0.0075)	(0.0092)	(0.011)
Black	-8.850***				
	(2.04)				
Hispanic	-3.873*				
	(2.25)				
Married	1.469	0.557	3.541	-1.422	-0.970
	(1.83)	(2.24)	(3.19)	(4.23)	(4.64)
Female	-6.181***				
	(1.27)				
Family Income	0.00000658	0.0000120	-0.00000124	0.0000113	0.0000104
	(0.000010)	(0.0000080)	(0.000010)	(0.000038)	(0.000018)
Lives with Mother	2.301	-1.359	-0.964	3.073	-5.782
	(4.74)	(4.73)	(6.01)	(9.86)	(11.5)
Mother's Education	1.545***	2.279*	0.917	0.889	2.927
	(0.40)	(1.24)	(1.69)	(2.46)	(2.58)
Urban	0.758	1.767	4.461	6.713	-5.786
	(1.75)	(2.09)	(2.89)	(4.69)	(5.31)
Constant	158.2***	111.8***	125.0***	96.18**	102.6***
	(25.0)	(20.1)	(28.0)	(47.2)	(39.6)
Sample	All	All	Boys only	Black	Hispanic
Specification	OLS	FE	FE	FE	FE
Observations	17468	17468	8755	5134	3355

Robust standard errors in parentheses are clustered at the family level.
*** p<0.01, ** p<0.05, * p<0.1

All specifications control for sex, birth order, ethnicity, living with mother, mother's marital status and education, and urban residence.

Table 5: Aizer Behavioral Index and Labor Market Participation

Dependent Variable	Aizer Behavioral Problem Index				
	(1)	(2)	(3)	(4)	(5)
Fraction of Year Employed	-0.0508** (0.026)	-0.0117 (0.040)	-0.133** (0.064)	-0.0643 (0.073)	-0.0172 (0.084)
Average Hours Per Week	0.00114** (0.00048)	-0.00114 (0.00086)	-0.000712 (0.0012)	-0.00166 (0.0018)	-0.00126 (0.0019)
Number of Siblings	0.0126** (0.0064)	-0.0518*** (0.020)	-0.0695** (0.034)	-0.0971*** (0.032)	-0.00345 (0.046)
Home Inventory Score	-0.000175*** (0.000051)	-0.000185** (0.000074)	-0.000146 (0.00012)	-0.000249* (0.00013)	-0.000120 (0.00015)
Black	0.0533*** (0.017)				
Hispanic	0.0382** (0.019)				
Married	-0.0373** (0.016)	0.0343 (0.035)	0.0714 (0.055)	0.0803 (0.056)	0.108 (0.070)
Female	-0.114*** (0.012)				
Family Income	-0.000000145 (0.00000010)	-0.0000000604 (0.00000012)	-0.000000246 (0.00000017)	-0.000000465* (0.00000026)	0.000000268 (0.00000027)
Lives with Mother	-0.0964** (0.041)	0.00654 (0.065)	-0.0572 (0.12)	-0.0572 (0.11)	0.0275 (0.15)
Mother's Education	-0.0125*** (0.0032)	0.0222 (0.019)	-0.00429 (0.031)	0.0295 (0.037)	-0.0144 (0.036)
Urban	0.0244 (0.015)	-0.00840 (0.029)	-0.0657 (0.048)	-0.113* (0.067)	0.0813 (0.059)
Constant	1.376*** (0.074)	1.100*** (0.26)	1.355*** (0.43)	0.393 (0.53)	1.650*** (0.50)
Sample **Specification**	All OLS	All FE	Boys only FE	Black FE	Hispanic FE
Observations	6011	6011	2966	1785	1204

Robust standard errors in parentheses are clustered at the family level.
*** p<0.01, ** p<0.05, * p<0.1
All specifications control for sex, birth order, ethnicity, living with mother, mother's marital status and education, and urban residence.

Essay 3

Family Size and 'Sibling Subsidization': Evidence from Rural India

Sumanta Mukherjee — **University of Kansas**

William A. Darity, Jr.[25] — **Duke University**

[25] Department of Public Policy, Duke University, P.O. Box 90239, Sanford School of Public Policy, Durham, NC 27708. (email: william.darity@duke.edu).

1. INTRODUCTION

In recent years, the phenomenon of child labor has received widespread attention in the academia.[26] Such attention probably stems from the appalling estimates of the number of child laborers in a world that boasts of unprecedented prosperity. The International Labor Organization (ILO), for instance, estimates that there were as many as 210 million child laborers (aged 5 through 14) around the world at the turn of the millennium (ILO 2002).[27]

The literature on child labor has focused heavily on policies aimed at the prevention of the continuation or extension of the phenomenon. It is unlikely that significant progress can be made in that direction without a proper appreciation of the economic and social factors that cause child labor. One of the well-documented proximate reasons for child labor is a shortfall in income from non-child labor sources.[28] What could bring about such a shortfall? Rose (1999) identifies rainfall shocks as an external mechanism that could bring about shortfalls in income and undermine consumption smoothing efforts. Theory suggests that even in the absence of any exogenous shock to *total* parental income, ongoing increases in family size for a couple during their reproductive years could lead to shortfalls in *per capita* incomes severe enough to force children to work.

However, identifying the exact causal relationship between family size and the child's labor supply decisions can be somewhat more complicated. The key difficulty in disentangling the relationship arises from the possibility that there could be unobserved processes that jointly influence decisions regarding fertility and sending children to work. The possibility cannot be

[26] The new wave of academic interest was probably prompted by Basu and Van (1998).

[27] The ILO estimate for the year 1990 was around 79 million child laborers internationally. Comparison with the more recent estimate points toward the pervasive failure to stem the phenomenon around the world.

[28] This in fact is the oft-quoted Luxury Axiom propounded in Basu and Van (1998).

ruled out that couples that have several children have a different attitude toward child work compared with those who would rather have only one or two children.

This paper primarily attempts to devise an instrumental variable solution to the endogeneity issue. The instrument we propose is premised on the idea that most rural households in East and South-East Asia prefer sons to daughters, particularly *until* they have their first male child.[29] If the first child is female, it appears quite likely (as we show with rural Indian data below) that the couple will procreate again. Under the circumstances, it seems reasonable to assume that the gender of the first child would be highly correlated with fertility (and hence family size) at least in rural India. Gender of the first child therefore could be a potential instrument for fertility in the implied regression equation.[30]

Preference for male children in rural India is likely a product of the existing system of social norms. A typical female in rural India gets married at a rather young age.[31] Thereafter she spends the rest of her life with her husband's (extended) family. In addition, marrying off a daughter almost always involves a lump sum dowry payment to the groom's family. Most important, there are important differences in labor market opportunities for and performances of females vis-à-vis the males in rural India. As pointed out by Ahn (1995), male children are preferred to female children in societies without organized social security arrangements, because of the higher expected support in old age. Since most people continue to live in their extended

[29] See Das (1987) for India, Park and Cho (1995) for Korea, Arnold and Zhaoxiang (1986) for China.

[30] The intellectual precursor to this instrument was first proposed in the labor economics literature. Angrist and Evans (1998), for instance, use the sex-composition of siblings as an instrument in the analysis of changes in family size and labor supply decisions. Their instrument is predicated on the idea that American couples like to *balance* the sex-composition of their children; this is in sharp contrast with the idea driving the choice of instrument in this study.

[31] Using NFHS data for 1992-93, Das and Dey (1998) report that the mean age at (first) marriage for women in rural India as 19.1 years. The median age at marriage is around 16 years.

family well beyond their earning years, it appears prudent to have a male child who would eventually bring a female into the family together with a sizeable dowry, earn higher labor income and be better equipped to take care of older relatives.

This paper uses household-level data on rural India from the 50th Round of the Employment and Unemployment Schedule of National Sample Survey Organization. We estimate a heteroskedasticity-robust linear probability model to quantify the impact of total fertility on the probability that the family sends the oldest child between the age 5 and 14 to work.[32] After controlling for indicators of wealth, education, infrastructural facilities, type of household (i.e. whether agricultural or industrial etc), household headship, caste and religion, the second stage regression results indicate that total fertility significantly affects any given child's probability of being sent to work. This therefore points to an interesting phenomenon, which we label the '*sibling subsidization effect*': a new child in the family significantly increases the probability that an older sibling will have to work to help support the family. The results for the first stage provide ample evidence that, at least in rural India, the gender of the first child significantly affects subsequent fertility decisions.

The remainder of the paper is organized as follows. Section II sets out the basic econometric framework. Data and descriptive statistics are outlined in Section III. Results and robustness checks are discussed in Sections IV and V. Section VI concludes.

[32] By restricting attention to the age group 5 through 14, the present study adheres to the ILO definitions.

2. EMPIRICAL STRATEGY

The first part of this section sets out the econometric framework that we employ to identify the effect of total fertility on child labor. In the second part, we discuss the dependent and independent variables included in our regression.

A. *Estimation Technique*

This paper explores the relationship between child work, W_i, and family size, S_i, conditional on other household characteristics, X_i:

$$W_i = \alpha + \beta S_i + \gamma X_i + \varepsilon_i \qquad (1)$$

The primary coefficient of interest is indeed β, but we hope to gain important insights from the sign and magnitude of γ as well. The coefficient β captures the effect of fertility on whether the oldest child in the family is sent to work. A positive (negative) β indicates that if family size increases (through procreation), then the oldest child in the family in the age group 5-14 would face a higher (lower) probability of being sent out to work, all else equal.[33]

There is, however, a problem in trying to estimate equation (1) using simple OLS. In order to derive a causal relationship between W and S, one has to assume that family size is exogenous, i.e. $E(\varepsilon \mid S, X) = 0$. But it is difficult to rule out the possibility that unobservable factors affecting fertility decisions have a role to play in influencing attitudes towards child work. In other words, family size and child labor supply decisions could be jointly determined. Under the circumstances, running OLS on equation (1) would produce biased estimates of both β and γ.

[33] This paper assumes that every child has an equal probability of being sent to work. What determines which child is sent to work is a question that begs an entire paper. See Basu *et al* (2003) for an analysis of birth order and child labor.

We suggest an instrumental variable solution to address this problem. The idea behind the instrument is that at least in rural India, couples prefer to have sons rather than daughters, especially until they have at least one son. Such a *male preference* originates from an existing structure of social norms that broadly dictates much of economic behavior. The fact that daughters typically have to be married off with a sizeable dowry, together with the fact that there may be extra-economic barriers to daughters taking care of their parents in old age could at least in part explain this attitude towards female offspring.[34] This perception of greater old age support probably provides the single most important incentive behind parental decisions to have at least one male child.[35] Consequently, if the first child is female, couples are likely to want to have another child thereby increasing family size.

It therefore appears reasonable to assume that the gender of the first child would be highly correlated with fertility (and hence family size) at least in rural India. If the gender of the first child is indeed a random variable, it could be used as a potential instrument for S_i in equation (1). In particular, we define an indicator variable F_i that takes the value 1 if the first child is female and 0 otherwise. We note here that the instrument uses the gender of the first child that is observed in the household. Using F_i as an instrument for S_i, we estimate a heteroscedasticity-robust 2SLS on equation (1) to derive consistent point estimates of the coefficients of interest.

[34] Women in rural India typically stay with their husbands' families (whereby they may well be geographically or at least informationally separated from their parents). As such, they are at a significant disadvantage vis-à-vis their male counterparts in regard to looking after their parents.

[35] In countries that are ridden by high infant mortality rates, a similar argument can explain the desire for multiple male children.

B. *A Brief Introduction to the Dependent Variable and the Included Regressors*

The dependent variable 'child' in our regression framework is a binary indicator for child labor. In particular, it takes a value 1 if the oldest child (in the age group 5-14) in the family works in his/her household enterprise or for a third party in the market. It is important to note that this oldest child is not necessarily the oldest child in the household: he/she is oldest child in the age group 5-14 that is observed in the household. The independent variable 'nchild' measures the number of children in the family.

In the absence of data on labor income for rural Indian households, we use the amount of land possessed by the household as a proxy, assuming it would be (at least broadly) indicative of wealth levels of rural households. Consequently, landholding is introduced as a quadratic polynomial, to capture a potentially nonlinear relationship (Basu *et. al*., 2003).

It may also be useful to know if certain particular types of household (categorized by primary occupation) are more closely associated with higher levels of child work. We have therefore divided households into four broad categories: agricultural laborers, self-employed in agriculture, employed in non-agricultural work and others.

Insofar as economic decisions in rural Indian families are mostly made by the head of the household and his/her spouse, it is critically important to account for their levels of education. All else equal, a highly educated parent (particularly a mother) is very likely to be averse to having his/her child interrupt school for work.[36]

Religion and caste can play important roles in shaping labor market behavior in rural India. People belonging to minority communities (like minority religious communities and/or

[36] In addition, the effect of parents' education on a child's school participation rates is potentially gender sensitive. In other words, in the event of making a choice regarding which child should be discontinued from school in response to a negative financial shock, a parent is often likely to interrupt his/her daughter's education (rather than the son's). The present analysis abstracts from these underlying gender issues. See Basu, Das and Dutta (2003) for an illuminating discussion on birth order and gender issues.

castes) may encounter institutional barriers to possessing or accessing resources that would usually be available to other communities at a lower cost. In addition, there could be different sets of norms that guide economic behavior among certain communities. A typical Muslim couple, for instance, may be far more averse to sending their female children out to work (because of possible religious inhibitions) than a comparable Hindu couple. Therefore we have included a set of indicator variables for minority religions and castes.

Finally, at least in the rural Indian context, households that are headed by women may have potentially different opportunities (and aspirations) than those headed by men. We identify households that are headed by women and often include a female headship indicator.

3. DATA

The data for this study is drawn from Employment and Unemployment Schedule of the National Sample Survey Organization (NSSO) for the year 1993-94 (the 50th Round). The Employment and Unemployment Schedules are administered throughout India (barring inaccessible regions) every five years by the Government of India. The present study however restricts attention only to rural India for reasons described above.

These Schedules are administered in four different sub-rounds, each lasting three months starting in July. In each sub-round, an equal number of households are selected by stratified random sampling for survey. Data are collected on household size and composition, household headship, indicators of unearned wealth and labor income, infrastructural facilities, indebtedness, social status, age, schooling, gender, marital status and employment details (type of employment, subsidiary employment, whether missing school for work, industry in which employed etc).

This study looks at families in rural India that have *at least one* child in the age group 5-14. The focus on this particular age group is in keeping with the International Labor Organization standards. Consequently our data is composed of 174,651 individuals making up 26,845 households (that have at least one child in the age group 5-14 in the year 1993-94).

Table 1 summarizes the means and standard deviations of some the key variables. In column 1, the means and dispersions of the variables for the entire sample are reported. In subsequent columns, we look at sub-samples that constitute minority communities. In particular, columns 2 and 3 report results for respectively the scheduled castes and tribes. Muslim households are looked at in columns 4. Finally column 5 pays attention to households that are headed by women. There appears to be a wide variation of child labor patterns across communities. For instance, the average incidence of child labor in lower caste households is well above the national average and substantially higher than other subgroups. Further, probabilities of child labor are substantially lower in Muslim households. Interestingly, total fertility does not show any remarkable variability across communities: most families in our sample have around 3.5 children.

There are, however, significant variations in landholding across communities. Clearly, other than scheduled tribes, most minorities have access to much less land, which could potentially indicate that these communities are essentially poorer. In addition, in the entire sample, the distribution of landholding is quite skewed. This point is illustrated in the pie chart in Figure 1.

Our data does not report education in terms of years of schooling. Instead, we have seven different categories: illiterate, below primary, primary, middle, secondary, post-secondary schooling and college education.[37] Figures 2 and 3 plot the respective distributions of education among heads of households and their spouses. The figures indicate that a disproportionate share of economic decision-makers in rural households is illiterate. Less than ten percent household heads have more than ten years of formal schooling. The numbers for their spouses are even lower.

Figure 4 plots child labor patterns against land possessed. The scatter diagram indicates a non-linear relationship between asset accumulation and child work. Children are more likely to work in families that own more land (probably because they have the opportunity to work); but eventually the marginal effect of wealth takes hold, reducing the probability of child work. Figure 5 illustrates the familiar impact of education of economic decision-makers on child labor patterns: child work probabilities decrease drastically if household heads are more educated. In

[37] To be precise, secondary and post-secondary levels refer respectively to ten and twelve years of school.

particular, there is very little child labor in families that are headed by people with college degrees.

4. RESULTS

A. *Correlation*

Table 2 reports the correlation matrix of key variables in the entire sample. The key result is the positive correlation between the number of children and the probability of child work. The overall pattern indicates a negative correlation between education of decision-making authorities and child work, as corroborated by Figure 4. Families that are headed by the more educated people are usually also the ones with more land. This is not surprising: the more affluent are usually the ones who have access to better schooling opportunities. Further, education of the household head and his/he spouse is negatively correlated with fertility. As mentioned in the previous section, the small positive correlation between land possessed and child labor is probably explained by the fact that families that own more land are in a better position to employ their children in their farms than the landless. The easy employability of children in useful agricultural activities is again borne out by the positive correlation between agricultural labor and child work.

One of the striking entries is the positive correlation between landholding and number of children. Economic theory has a long tradition in predicting a reverse pattern, suggesting that parents care more about quality of children rather than quantity as their wealth levels rise (Becker and Lewis, 1973). On the other hand, in the context of rural India, one could argue that having more children is a plausible way of making a statement about one's financial capabilities.

Finally, the female headship dummy is usually negatively correlated with all the included regressors, indicating thereby that these households are poorer in both wealth and education and that they have fewer children. But, interestingly, the female headship dummy is negatively (although weakly) correlated with child work.

B. *Discussion of OLS and 2SLS Estimates*

Before we report the 2SLS results, let us examine the strength of our instrument. A well-documented concern with the IV technique is that even in large samples, IV estimates could be inconsistent if the instruments are weak. To see how our instrument performed, we focus on the first stage results reported in Table 3. The indicator for whether the first child was a female enters with a positive and highly significant coefficient in all the three groups. In particular, for the entire sample it implies that all else equal, couples that had their first offspring as female ended up having 0.26 more children (which is significant at the 1% level). This suggests that our instrument is not weak and that our first stage has good power.

Table 4 reports the OLS and 2SLS estimates of β and γ for the benchmark specification in equation (1). For the purpose of comparison, we report the results for male-headed and female-headed families as well. The dependent variable is simply a binary indicator for child work.

The OLS estimates indicate a weakly positive but very significant impact of having an extra child on the probability of sending the oldest child to work, after controlling for wealth, education and other covariates. In particular, it implies that all equal, a family (with at least one child in the age group 5-14) that has one extra child would be 2.1% more likely to send any one of its children to work.

The primary income indicator, per capita total cultivated land interestingly enters with a significant positive (although small) coefficient; the negative coefficient for the quadratic term is not surprising. The positive coefficient on land possessed, though apparently surprising, echoes the claims made by Bhalotra and Heady (2002) in their analysis of land ownership and child labor in Pakistan and Ghana. In the absence of a properly functioning labor market, operating large amounts of land could imply, as Basu and Tzannatos (2003) suggest, "…having the opportunity for more productive use of the household's labor, including child labor." The agricultural laborer indicator appears with a statistically significant positive coefficient, again possibly bearing out the fact that agricultural families may have better way to utilize their children's services.

Among other controls, the education levels of the head of the family and his/her spouse appear to have a very significant negative effect on the probability that a child is sent to work, which is not unexpected.

Religious minorities evidently appear more averse to child work vis-à-vis the Hindus, part of which can be attributed to possible religious inhibitions. The coefficients for the scheduled castes and tribes indicators are positive and significant (for the tribes). These minority communities, who refer to the lowest rung of the caste system in India, mainly constitute the craftsmen. A likely explanation of the positive estimates is that, at least in the perception of the working class, being trained in the parent's craft since childhood is a more appropriate investment in human capital than formal school-based education. This may be compounded by the possibility of low rates of return to schooling (or at least the fact that returns do not kick in early enough), which affect parents' choices for utilizing a child's time (Chamarbagwala, 2004).

The households headed by men have broadly the same pattern as in the pooled sample. The results are more interesting for the households headed by women. The coefficient for fertility is weakly positive and statistically insignificant. The education of the head is still an important determinant of child work. However, the fact that schooling levels of the heads' spouses do not matter (statistically) appears to point to a skewed importance of the female head in making economic decisions in the family.

The OLS estimates bear out the hypothesis that total fertility positively affects the probability of child labor. However, these estimates could reflect the impact of unobserved household characteristics that jointly determine work and fertility decisions. Consequently we ran a 2SLS regression using the gender of the first child as an instrument for total fertility. The 2SLS estimates paint a broadly similar picture, the differences showing primarily in the significance levels.

The 2SLS estimates indicate that the impact of having an extra child on the probability of child work is substantially higher than that suggested by the OLS regression. To be precise, 2SLS suggests that all else equal, a family (with at least one child in the age group 5-14) is 5.26% more likely to send a child to work, if it has an extra child. It is this phenomenon that we refer to as ‘sibling subsidization’: de facto, an older child is subsidizing the presence of a newer child.

5. ROBUSTNESS

In this section we test the robustness of our OLS and 2SLS estimates to the choice of different specifications. Table 5 reports the standard robustness check after controlling for some additional variables and interactions. Bhalotra and Heady (2002) recognizes landholding as an important indicator of wealth and shows that children of landowners are less likely to be in school than the children of poor landless households. While our benchmark model mirrors this 'wealth paradox', we think it might be useful to explore the possibility that landholding may affect child work through its interaction with number of existing children. We also allow parental education to affect child work through their interaction with number of children.

In addition, we incorporate some other variables that indicate the level of infrastructural facilities and/or income available to the households. The availability of electricity, for instance, is a likely indicator of the levels of infrastructural facilities that are available to a particular village or group of villages. In similar vein, the availability of latrines is an inevitable indication of higher income. We have therefore included indicators for electricity and latrines in the extended model.

The results of the robustness check are encouraging. The total fertility variable is still significant at the 5% level by itself in both the OLS and 2SLS regressions. With the introduction of interactions, land and parental education become insignificant by themselves. The negative coefficient for the interaction term between land and fertility indicates that the richer the household, the lower the probability of sending the oldest child to work in response to having an additional child. Similarly, the negative coefficient for the interaction between parental education and fertility implies that the more educated the parents, the lower the probability of interrupting the oldest child's schooling in response to having an additional child. Finally, the coefficients for electricity and availability of latrine are significant and have expected signs.

We also split the sample by gender to examine the differential incidence of child labor across gender. The results (not reported) indicate expected signs, but the marginal effects are not statistically significant for either gender. In other words, the sibling subsidization effect ceases to be statistically significant for the two subpopulations.

6. CONCLUDING REMARKS

This paper used a linear probability model to explore the relationship between family size and child labor. We found that having an additional child significantly increases the probability of labor force participation of existing children. To the extent that total fertility is determined by a preference for male children, it seems reasonable to direct policy towards educating household decision-makers not only to stem population growth but more importantly to treat children equally regardless of gender. Such perceptions of inequality are however bound to persist as long as labor market opportunities for adult women are not substantially improved. This is not only because increased job opportunities would allow adult daughters to be economically more flexible to look after parents, but because at a deeper level it would improve the bargaining power of women, which may have a crucial role to play in stemming population explosion and increasing child welfare.

Almost inextricably related is the issue of raising immediate rates of return to schooling. An important excuse for interrupting a child's education is premised on the belief that beyond literacy, children do not learn 'useful stuff' at school. Efforts to incorporate vocational training in the curriculum could in part mitigate this problem. Further, programs like free mid-day meals at school could provide important incentives to poor parents to send their children to school.

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Table 1: Means and Dispersions of Important Variables

Variable	Total[1]	Scheduled Castes[2]	Scheduled Tribe[3]	Muslims[4]	Female Headed[5]
Child Labor	0.1271	0.1494	0.1657	0.1088	0.1155
	(0.3332)	(0.3565)	(0.3718)	(0.3114)	(0.3196)
Number of Children	3.7159	3.6717	3.3276	3.6573	3.4066
	(1.4977)	(1.4128)	(1.4615)	(1.5169)	(1.4626)
Landholding	184.4832	72.4493	168.9953	91.6003	86.1416
	(625.8585)	(168.0092)	(368.1609)	(246.4776)	(166.9112)
Education of Head	2.3781	1.8936	2.1653	2.1816	1.6456
	(1.6555)	(1.3639)	(1.4993)	(1.5253)	(1.2014)
Education of Spouse of Head	1.4494	1.1866	1.4830	1.3821	0.1105
	(1.1657)	(0.8237)	(1.1139)	(1.0891)	(0.5778)
Agricultural Laborers	0.2123	0.4082	0.2267	0.1942	0.2078
	(0.4089)	(0.4915)	(0.4187)	(0.3956)	(0.4057)
Non-Agri Laborers	0.1327	0.1247	0.0060	0.2222	0.0669
	(0.3392)	(0.3304)	(0.2484)	(0.4158)	(0.2498)
Access to Latrine	0.2391	0.1362	0.3179	0.3662	0.2429
	(0.4265)	(0.3429)	(0.4656)	(0.4818)	(0.4289)
Electricity	0.4283	0.3091	0.3685	0.3199	0.4847
	(0.4948)	(0.4621)	(0.4824)	(0.4665)	(0.4998)

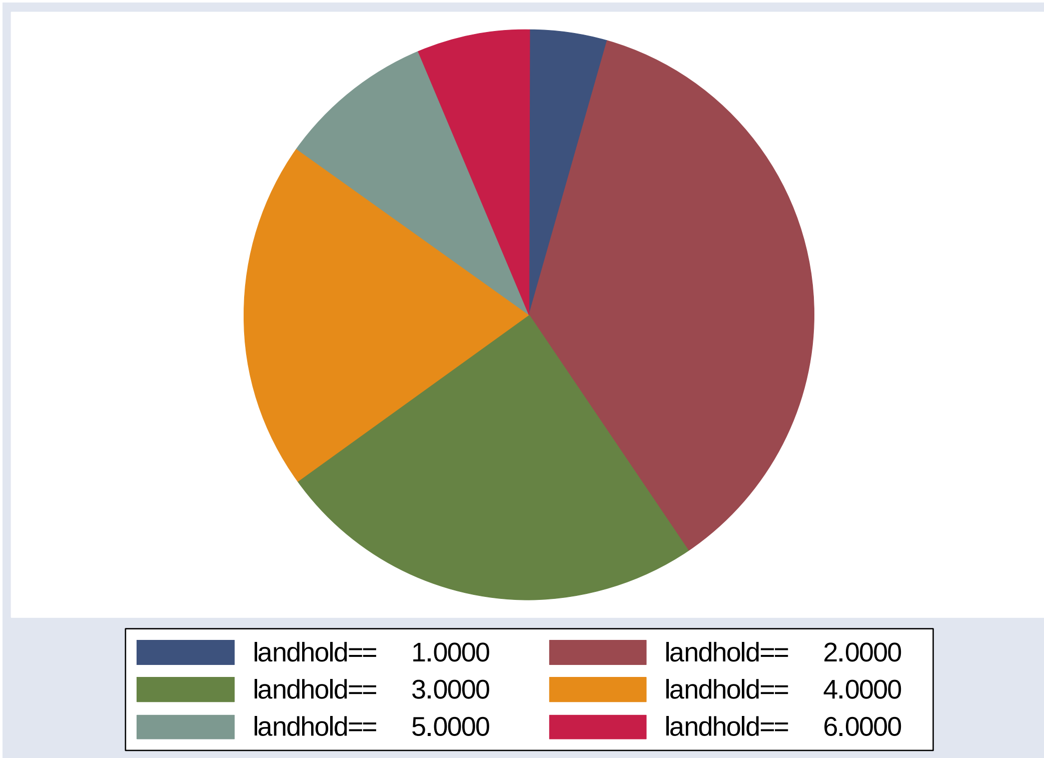
[1] Sample size 26,845; [2] Sample size 4,762; [3] Sample size 3,813; [4] Sample size 2,897; [5] Sample size 1,999

Table 2: Correlation Matrix

	child	nchild	totland	educhd	educsp	aglab	nonag	muslim	femhd
child	1.000								
nchild	0.092	1.000							
totland	0.002	0.018	1.000						
educhd	-0.14	-0.007	0.033	1.000					
educsp	-0.103	-0.026	0.028	0.569	1.000				
aglab	0.056	-0.053	-0.119	-0.227	-0.123	1.000			
nonag	-0.025	0.024	-0.074	0.065	0.079	-0.195	1.000		
muslim	-0.021	0.145	-0.036	-0.040	-0.019	-0.013	0.092	1.000	
femhd	-0.009	-0.051	-0.039	-0.109	-0.283	0.002	-0.049	0.031	1.000

Note: child = indicator for child labor; nchild = # of children; totland = amount of land owned; educhd = education of head of household; educsp = education of spouse of head; aglab = agricultural labor dummy; nonag = non-agri labor dummy; femhd = female headship dummy

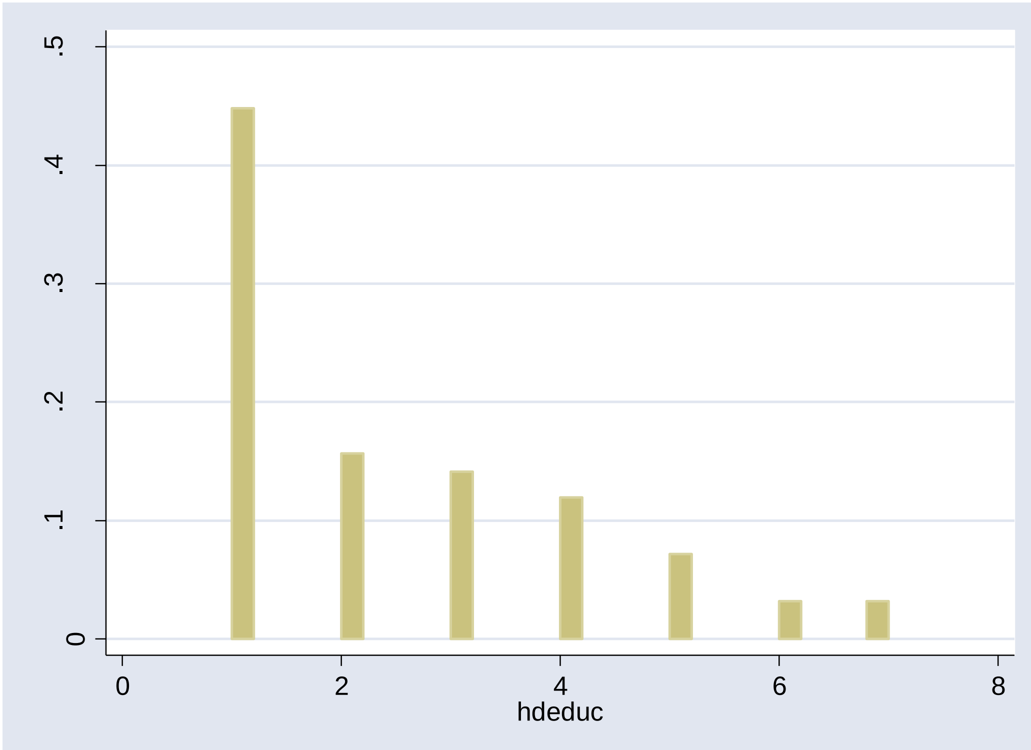
Figure 1: Distribution of Landholding in the Entire Sample



Note:

Code	Landholding in acres
1	Landholding = 0
2	50>Landholding>0
3	150>Landholding>50
4	400> Landholding>150
5	1000>Landholding>400
6	Landhold>1000

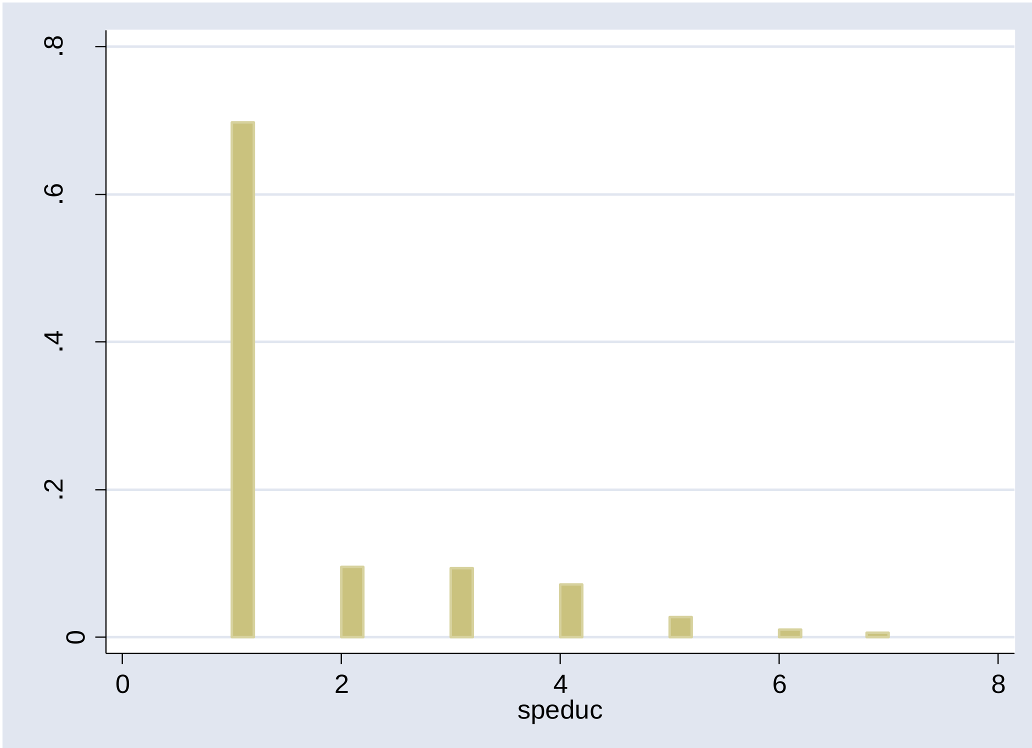
Figure 2: Distribution of Education among Household Heads in Total Sample



Note:

Code	Education
1	Illiterate
2	Below Primary
3	Primary
4	Middle
5	Secondary
6	Post-Secondary
7	College

Figure 3: Distribution of Education among Spouses of Heads in Total Sample



Note:

Code	Education
1	Illiterate
2	Below Primary
3	Primary
4	Middle
5	Secondary
6	Post-Secondary
7	College

Table 3: First Stage Results

Dependent Variable	Pooled	Male-Headed	Female-Headed
Female	0.2484*** (0.0167)	0.2506*** (0.0174)	0.3297*** (0.0575)
Land	0.0002 (0.0002)	0.0002 (0.0003)	0.0009 (0.0004)
Education of Head	0.007 (0.0033)	0.0099 (0.0034)	-0.0294** (0.0118)
Education of Spouse of Head	-0.0326*** (0.0042)	-0.0486*** (0.0044)	0.0024 (0.0314)
Agricultural Laborer	-0.1249*** (0.0272)	-0.1525*** (0.0288)	-0.3012*** (0.0837)
Scheduled Castes	0.1326*** (0.0237)	0.121*** (0.0247)	0.1244 (0.0817)
Scheduled Tribes	0.1276*** (0.0282)	0.1122*** (0.0292)	0.0173 (0.1075)
Muslim	0.6537*** (0.0281)	0.6925*** (0.0296)	0.3926*** (0.0875)
Age of Child	-0.0139*** (0.0005)	-0.0138*** (0.0005)	-0.0196*** (0. 0017)
N	26844	24846	1998

Notes: Robust SEs in parentheses. The dependent variable is an indicator equal to 1 if oldest child aged 5 – 14 is working. N = # of Households.

Table 4: Linear Probability Regression

	Pooled		Male-Headed		Female-Headed	
	OLS	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**
Number of children	0.022*** (0.0015)	0.0554*** (0.0165)	0.0229*** (0.0016)	0.0644*** (0.0172)	0.0059 (0.0054)	-0.0274 (0.0445)
Land	0.0001 (7.48e – 06)	0.0001 (7.91e – 06)	0.0001 (7.51e – 06)	8.99e – 06 (7.76e – 06)	0.0001 (0.0001)	0.0001 (0.0001)
Land Squared	-2.06e – 10 (7.93e – 11)	-1.21e – 10 (8.54e – 11)	-1.89e – 10 (7.97e – 11)	-9.67e – 11 (8.38e – 11)	-1.04e – 07 (6.83e – 08)	-1.01e – 07 (6.96e – 08)
Education of Head	-0.0216*** (0.0013)	-0.0218*** (0.0013)	-0.0217*** (0.0014)	-0.0226*** (0.0015)	-0.0199*** (0.0041)	-0.0221*** (0.0049)
Education of Spouse of Head	-0.0088*** (0.0015)	-0.0054*** (0.0009)	-0.0072*** (0.0008)	-0.0054*** (0.0011)	-0.0066 (0.0058)	-0.0066 (0.0058)
Agricultural Laborer	0.0278*** (0.0063)	0.0317*** (0.0067)	0.0136** (0.0068)	0.0202** (0.0073)	0.1357*** (0.0214)	0.1257*** (0.0247)
Scheduled Castes	0.0115 (0.0058)	0.0058 (0.0063)	0.0079 (0.0061)	0.0032 (0.0064)	0.0268 (0.0218)	0.0319 (0.0227)
Scheduled Tribes	0.0616*** (0.0076)	0.0575*** (0.0079)	0.0641*** (0.0079)	0.059*** (0.0082)	0.0201 (0.0263)	0.0202 (0.0269)
Muslim	-0.0378*** (0.0062)	-0.0586*** (0.0121)	-0.038*** (0.0066)	-0.0649*** (0.0131)	-0.0233 (0.0189)	-0.0131 (0.0243)
Age of Child	0.0001 (0.0001)	0.0006** (0.0003)	0.0001 (0.0001)	0.0007*** (0.0002)	0.0003 (0.0004)	-0.0003 (0.001)
N	26845	26844	24846	24846	1999	1999

Notes: Robust SEs in parentheses. The dependent variable is an indicator equal to 1 if oldest child aged 5 – 14 is working. N = # of Households.

Table 5: Test of Robustness

	Pooled		Male-Headed		Female-Headed	
	OLS	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**
Number of children	0.0327*** (0.0028)	0.1681** (0.0672)	0.0366*** (0.0031)	0.2197*** (0.0789)	0.0114 (0.0091)	-0.1491 (0.2246)
Land	8.34e - 07 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)	-0.0003 (0.0005)
Land * Children	3.66e – 06 (4.09e – 06)	-0.0003 (0.0002)	2.80e – 06 (4.17e – 06)	-0.0005 (0.0002)	0.0001 (0.0003)	0.0001 (0.0002)
Education of Head	-0.0014 (0.0033)	-0.0872 (0.0441)	-0.0022 (0.0026)	-0.1023 (0.0451)	-0.0017 (0.0109)	-0.1793 (0.2493)
Head Educ. * Children	-0.0052 (0.0009)	-0.0301 (0.0123)	-0.0051 (0.0009)	-0.0341 (0.0125)	-0.0022 (0.0018)	0.0135 (0.0235)
Education of Spouse of Head	-0.0082 (0.0041)	-0.0548 (0.0317)	-0.0025 (0.0022)	-0.1039 (0.467)	-0.0133 (0.0303)	-0.0136 (0.0376)
Spouse Educ.* Children	-0.0004 (0.0013)	-0.0213 (0.0109)	-0.001 (0.0006)	-0.0371 (0.0154)	0.0003 (0.0051)	0.0019 (0.0062)
Agricultural Laborer	0.0211 (0.0064)	0.0297 (0.0082)	0.0069 (0.0069)	0.0193 (0.0092)	0.1302 (0.0216)	0.1109 (0.0341)
Latrine	-0.0414 (0.0043)	-0.0442 (0.0048)	-0.0409 (0.0045)	-0.0458 (0.0053)	-0.0402 (0.0159)	-0.0389 (0.0166)
Electricity	-0.0084 (0.0042)	-0.0086 (0.0042)	-0.0085 (0.0045)	-0.0083 (0.0048)	0.0018 (0.0151)	0.009 (0.019)
Scheduled Castes	0.0089 (0.0059)	0.0073 (0.0061)	0.0082 (0.0061)	0.0056 (0.0064)	0.0236 (0.0218)	0.0237 (0.0242)
Muslim	-0.0319 (0.0062)	-0.057 (0.0142)	-0.0323 (0.0066)	-0.0656 (0.0159)	-0.0129 (0.0195)	0.0035 (0.0315)
Age of Child	0.0002 (0.0001)	0.0008 (0.0003)	0.0001 (0.0001)	0.0009 (0.0004)	0.0004 (0.0004)	-0.0007 (0.0017)
N	26832	26844	24833	24833	1999	1999

Notes: Robust SEs in parentheses. The dependent variable is an indicator equal to 1 if oldest child aged 5 – 14 is working. N = # of Households.